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Ideology and Interests:
A Hierarchical Bayesian Approach to Spatial Party Preferences

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Ideology and Interests:
A Hierarchical Bayesian Approach to Spatial Party Preferences

by

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Report

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Abstract

Ideology and Interests:
A Hierarchical Bayesian Approach to Spatial Party Preferences

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This paper presents a spatial utility model of support for multiple political parties. The model includes a "valence" term, which I reparameterize to include both party competence and the voters' key sociodemographic concerns. The paper shows how this spatial utility model can be interpreted as a hierarchical model using data from the 2009 European Elections Study. I estimate this model via Bayesian Markov Chain Monte Carlo (MCMC) using a block Gibbs sampler and show that the model can capture broad European-wide trends while allowing for significant amounts of heterogeneity. This approach, however, which assumes a normal dependent variable, is only able to partially reproduce the data generating process. I show that the data generating process can be reproduced more accurately with an ordered probit model. Finally, I discuss trade-offs between parsimony and descriptive richness and other practical challenges that may be encountered when

building models of party support and make recommendations for capturing the best of both approaches.

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Chapter One: Introduction

This paper presents a spatial utility model of support for multiple political parties. The model includes a “valence” term, which I reparameterize to include both party competence and the voter’s key sociodemographic concerns. The paper uses data from the 2009 European Elections Study to show how this spatial utility model can be interpreted as a hierarchical model using (European Elections Study, 2013). I estimate this model via Bayesian Markov Chain Monte Carlo (MCMC) using a block Gibbs sampler and show that the model can capture broad European-wide trends while allowing for significant amounts of heterogeneity. The findings suggest that ideology and interests usually have a larger effect than party competence but that the latter cannot be discounted in competitive environments. This approach, however, which assumes a normal dependent variable, is only able to partially reproduce the data generating process. This happens because of the high frequency with which voters report there is little to no chance that they will vote for the party in question. I show that the data generating process can be reproduced more accurately with an ordered probit model. Finally, I discuss practical challenges and trade-offs between parsimony and descriptive richness that may be encountered when building models of party support and make recommendations for capturing the best of both approaches.

Chapter Two: Theory

The model presented in this paper draws from existing spatial theory that holds that one's ideological proximity to a candidate or a party is a major determinant of one's propensity to vote for that candidate or party.[1] The spatial utility model is as follows: each voter has a $(1\ x\ p)$ utility vector, $\boldsymbol{u}_i$, which captures the distance between her ideal point, x_i, and each party's position, z_j, in k-dimensional space. In this paper, $k = 2$, with one dimension that runs from (the political) left to right and another dimension for position on European Union integration.

The model assumes that the dimensions of the policy space are orthogonal, which implies that there is zero correlation between the dimensions. Orthogonal dimensions can be obtained via principal components analysis which rotates the observed data (Johnston, 1984, p. 536ff). However, since the sample correlation between respondent's left-right and EU ideal points is only 0.0145, for the purposes of this analysis, it will be assumed that the dimensions are in fact orthogonal.[2] When the axes are orthogonal, the shortest distance between the voter's ideal points and each party's position can be obtained using the Pythagorean Theorem. If $x_i = \begin{pmatrix} LR_i \\ EU_i \end{pmatrix}$

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[1] For an introduction, see, for example, Hinich and Munger (1997).

[2] Another approach is to perform a two stage estimation, where the first stage is an ideal point model of both the parties and the individuals. However, as Jessee (2010, 332) notes, this produces noisy estimates even with 10 policy positions, and since only 2 are used here, I decided to leave the dimensions unchanged.

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and $z_j = \begin{pmatrix} LR_j \\ EU_j \end{pmatrix}$, then subtracting x_i from each vector centers the ideal point at the origin and yields expressions for each side of a right triangle:

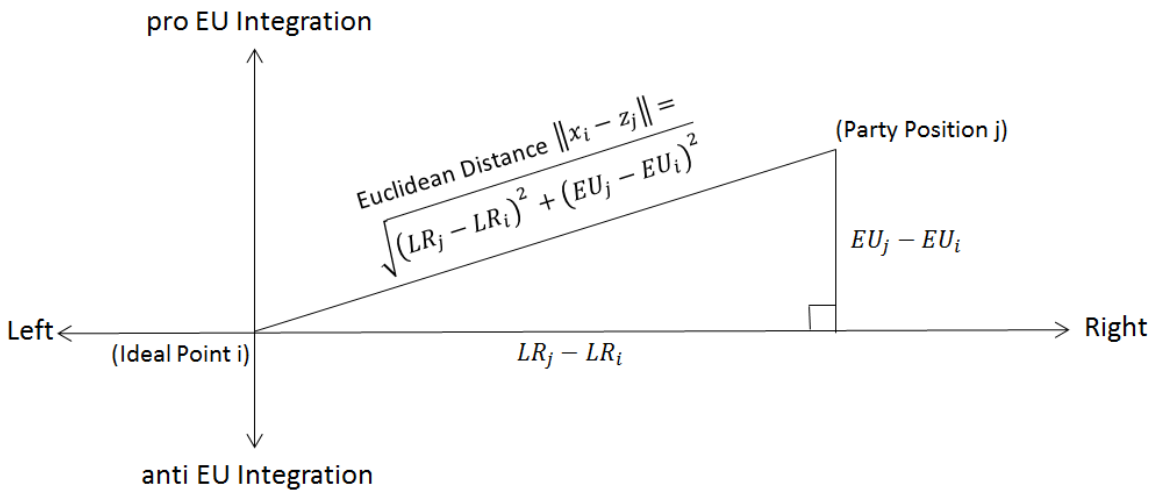

Figure 1: Spatial Distance between Voter i and Party j

The (two-dimensional) Euclidean distance, also known as the norm of the two vectors, is

$$\|x_i - z_j\| = \sqrt{(x_i - z_j)'(x_i - z_j)} = \sqrt{(LR_j - LR_i)^2 + (EU_j - EU_i)^2}$$

Distance can be connected to utility by adding a slope coefficient, β, such that $u_{ij}(x_i, z_j) = -\beta\|x_i - z_j\|^2$. β captures the effect of squared distance on utility and is assumed to be negative so that utility is an increasing function of $-\beta$.[3] The slope coefficient captures the importance of ideological distance and the fact that ideological distance and utility may not be measured in the same units. Put differently, the farther a voter is from any given party, in terms of ideological

[3] That is, $\frac{\partial u_{ij}(x_i, z_j)}{\partial\|x_i - z_j\|^2} = \beta < 0$

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distance, the less likely he is to support that party because supporting that party would give her less utility (than supporting a party she is closer to).

This paper adopts the "valence" model on the rationale that, in addition to ideological proximity, each individual *i* attaches a particular "valence" to each party *j* (λ_{ij}), which is the amount of utility that person *i* gets for party *j* above and beyond that which is captured by the ideological term (Jessee, 2010, p. 328). Schofield interprets λ_{ij} as a measure of "competence" (Schofield, 2004, p. 448). Voters may feel more inclined to vote for parties that have a chance of getting elected, of making a difference in parliament, and so on, and so may not vote for their ideologically preferred candidate. As discussed in more detail below, I interpret λ_{ij} widely to incorporate interests and identities. A first- or second-generation immigrant, for example, may consider himself to be quite conservative—and so appear to be ideologically proximate to parties on the right—but would nevertheless be unlikely to vote for rightist parties, many of which campaign in Europe today for a tough line on immigration.

In the spatial valence model, the utility function of voter *i* with respect to party *j* is

$$u_{ij}(x_i, z_j) = \beta_0 - \beta_1 \left\| x_i - z_j \right\|^2 + \lambda_{ij}$$

$\left\| x_i - z_j \right\|^2$ is the squared Euclidean distance between the voter's ideal point and the party's position. λ_{ij} is normally distributed with mean λ_j. Each λ_j has an associated stochastic variation term ε_j with mean zero. ε_j has variance σ_j^2 and each ε_j is

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uncorrelated with the others ($\varepsilon_j \varepsilon_{j'} = 0 \; \forall \; j \neq j'$). Here an overall intercept, β_0, is included, which centers the distribution of λ_j at 0. The probability that *i* picks *j* (considered as a function of party positions **z**) is

$$\rho_{ij}(\boldsymbol{z}) = Prob\left[u_{ij}\left(x_i, z_j\right) > u_{ij}\left(x_i, z_{j'}\right)\right] \forall \; j \neq j'$$

and, V_j, the expected vote share of party *j*, is the mean of those probabilities,

$\frac{1}{n}\sum_{i=1}^{n} \rho_{ij}(\boldsymbol{z})$.

Unlike distance, which requires a slope coefficient to be translated into utility, λ_{ij} is, by construction, already in utiles. For illustration's purpose, suppose $\beta_0 = 0$ and $\beta_1 = 1$, so that $u_{ij}\left(x_i, z_j\right) = -\left\|x_i - z_j\right\|^2 + \lambda_{ij}$. A one unit increase in distance will lead to a one unit decrease in utility, but this can always be offset by a matching increase in party valence. Equivalently, distance $d_{ij}\left(x_i, z_j\right) = \left\|x_i - z_j\right\|^2 - \lambda_{ij}$. Suppose that two parties, *j* and *j**, are equally far away from the respondent's ideal point in terms of ideological distance but that $\lambda_{ij*} < 0 < \lambda_{ij}$. Below, Figure 2 shows this situation in which the respondent prefers *j* even though both parties fall on the same indifference curve.

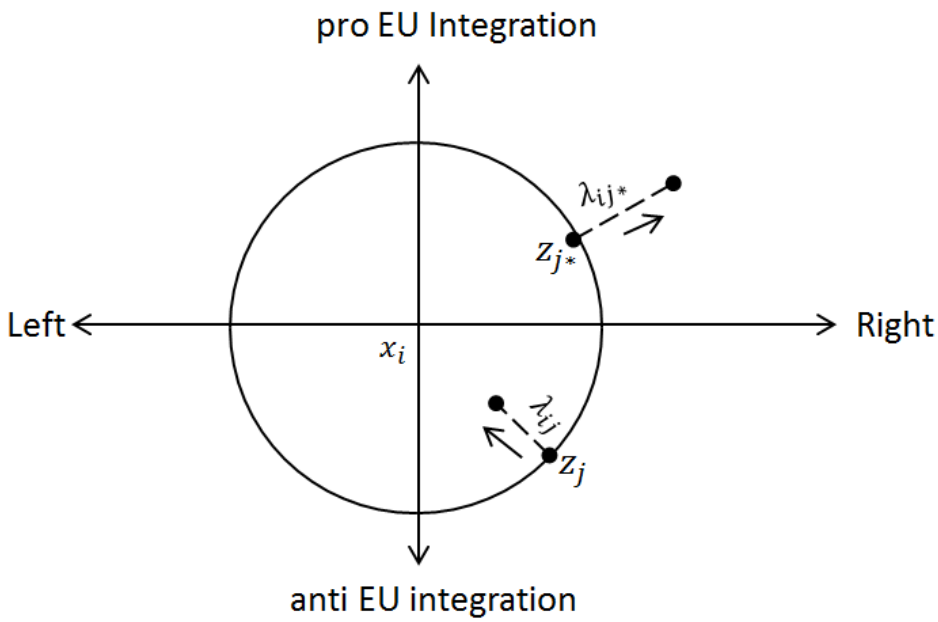

Figure 2: Spatial Distances with Party Valences

More generally, in the model without the valence term, distance implies an *indifference curve*: voters are theorized to be indifferent to parties taking positions on anywhere on the origin circle that has $\|x_i - z_j\|^2$ as the hypotenuse since all points on that circle have equal utility. However, once valence terms are added, voters have an *indifference set*: they are indifferent to any combination of distance and valence that has equal utility (since comparisons are relative, the intercept is never relevant). Though in principle infinite solutions are possible, the normal distribution of λ_{ij} makes solutions centered around λ_j much more probable. In general, given that individual *i* has a certain valence towards party *j*,

$$E\left(u_{ij}(x_i, z_j)\middle|\lambda_{ij}\right) = \beta_0 - \beta_1\|x_i - z_j\|^2 + \lambda_j$$

Further, by the Law of Iterated Expectations,

$$EE\left(u_{ij}(x_i, z_j)\middle|\lambda_{ij}\right) = \beta_0 - \beta_1 \left\|x_i - z_j\right\|^2$$

$$= \mu$$

where μ is the mean utility of the population.[4]

FROM SPATIAL UTILITY MODEL TO HIERARCHICAL REGRESSION MODEL

This spatial model can be easily interpreted as a hierarchical model if the effect of spatial distance, $-\beta\left\|x_i - z_j\right\|^2$, is considered the ground level of the model and party valence, λ_{ij}, is considered as a group level effect. Just as we would expect ideology to work relatively consistently across an individual's evaluation of multiple parties, we would expect responses about any given party to share certain characteristics. The mean of the distribution of responses about a party reflects its popularity, and the variance reflects how polarized the public is about the party. The mean of each party valence, λ_j, can then be reparameterized to include predictors. I include four individual characteristics here (the sociodemographic variables of class, education, migrant background, and European—as opposed to national—identity).

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4 In this case, the heterogeneity introduced by each individual having a valence towards each party can be summarized succinctly using the Law of Iterated Expectation, which holds that for any two random variables X and Y, where Y conditions X, the expectation of the conditional expectation is equal to the unconditional mean of X: $E\big(E(X|Y)\big) = EX$. λ_{ij} and λ_j are both random variables but, since $\lambda_{ij} \sim N(\lambda_j, \sigma_j^2)$ and λ_j is distributed normally with mean zero, if we know which party the individual is evaluating, we can say $E\left(E\left(\lambda_j|\lambda_{ij}\right)\right) = 0$, which simplifies the model as described above. See Casella and Berger (2002, 162ff).

The unit of observation is individual *i's* evaluation of party *j*. In a Gaussian linear multilevel model, the i,j[th] observation can be represented as following a normal distribution where the structural part of the ground level equation is the mean of the distribution:

$$u_{ij}(x_i, z_j) \sim N\left(\beta_0 - \beta_1\left\|x_i - z_j\right\|^2 + \lambda_{ij}, \sigma_u^2\right)$$

$$\lambda_{ij} \ = \ b_{0,j} + b_{1,j}w_i^{European} + b_{2,j}w_i^{edu} + b_{3,j}w_i^{class} + b_{4,j}w_i^{migrant}$$

$\beta_0 - \beta_1\left\|x_i - z_j\right\|^2$ can be written as the inner product of a design matrix of exogenous observations and a vector of slope coefficients, that is, as $X_i\boldsymbol{\beta}$. λ_{ij} can be expressed similarly as the inner product of a design matrix of observations on the individual, $\boldsymbol{W}_i$, and associated slope coefficients for each party, $\boldsymbol{b}_i$. This allows the model to be written as a longitudinal mixed effects regression model for the i^{th} individual where

$$y_i = X_i\boldsymbol{\beta} + W_i\boldsymbol{b}_i + \boldsymbol{\varepsilon}_i$$

y_i is a $\left(1 \ x \ n_p\right)$ vector of propensities and $\boldsymbol{\varepsilon}_i$ is the corresponding error term (one row for each party). $\boldsymbol{\varepsilon}_i \sim \mathrm{MVN}(0, \sigma^2 I_{n_p})$. $\boldsymbol{b}_i$ is also distributed multivariate normal with mean zero and variance convariance matrix *D*; *D* is a (5 x 5) matrix since there is an intercept in addition to the four sociodemographic predictors (Chib & Carlin, 1999).

One of the assumptions that underlies Bayesian regression is conditional independence: y_j and $\boldsymbol{x}_j$ contain no additional information about y_i beyond what is contained in $\boldsymbol{x}_i$ and the parameters, $\boldsymbol{\theta}_{y|x}$, for all $i \neq j$ (Jackman, 2009, p. 100). This assumption would be violated if the hierarchical nature of the data was not modeled. One way to illustrate this violation, following Gelman and Hill (2009, 265), the variance covariance matrix, Σ, can be characterized

$$\Sigma_{ij,ij} = \begin{cases} \sigma_u^2 + \sigma_j^2 & for\ ij = ij\ \ (variance\ of\ each\ observation) \\ \sigma_j^2 & for\ j = j, but\ i \neq i\ (covariance\ of\ responses\ for\ each\ party) \\ 0 & otherwise. \end{cases}$$

If no second level predictors are included, as is the case in a basic varying intercept in the model, D simplifies to a single variance term, σ_j^2. Otherwise σ_j^2 is the composite implied by the linear combination of (the normally distributed elements of) $\boldsymbol{b}_i$ and the data, W_i, which is treated as constant. If $\sigma_j^2 = 0$ (no effect of party valences), the structural model simplifies to $\beta_0 - \beta_1 \|x_i - z_j\|^2$ with homoscedastic, non-autocorrelated errors (provided σ_u^2 is constant for all observations). Without the influence of λ_{ij}, the model becomes similar to that described by Lin, Enelow, and Dorussen (1999).

More intuitively, the most basic spatial model described at the opening assumes the following stylized decision-making process: individuals evaluate one party at a time and then later rank them based on their relative utilities. Party valences are included on the expectation that they are something of a tie-breaker. For example, an ideological leftist would prefer a viable centrist party to an ineffectual, but ideologically more proximate, leftist party (but probably not a rightist party, even one that is highly competent). Similarly, sociodemographic characteristics are included on the assumption that they contain additional information about the ideology and interests of voters that is not captured by distance. The model here still reflects the idea that voters determine party utilities one at a time and then make their vote choice based upon the resulting ranks. Put differently, it is unnecessary to model party utilities endogenously as a function of (at least some of) the other party utilities because each individual has an intercept towards each party, λ_{ij}, which properly offsets the party ranks.[5]

λ_{ij} reflects both strategic and sincere voting. Since $\mathrm{E}\lambda_j = 0$, if $\widehat{\lambda_j} > 0$, it can be taken as evidence that party *j* is thought to be more competent than the mean party. In particular, the party intercept $b_{0,j}$ may be interpreted as party *j*'s competence, and hence *strategic* support, while the magnitude of $b_{1,j}$, $b_{2,j}$, $b_{3,j}$, and $b_{4,j}$ (along with β_1), may be taken as evidence of *sincere* voting.

BAYESIAN ANALYSIS OF HIERARCHICAL MODELS

Sometimes we can update our beliefs about a probability when we have been given additional information (a condition). The conditional probability is the probability that both the condition and the event occur divided by the probability of the condition. Formally, for two events A and B in a sample space S where $\mathrm{P(B)} > 0$:

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[5] This would be violated, for example, if voters liked or disliked certain parties for no discernible reason other than their attitude towards some other party (that is, party loyalty that could not be expressed in terms of ideology or interest). This would also be violated if y_{ij} depended on some interaction of $y_{ij'}$ and $\lambda_{ij'}$ (that is, if fear of the competence of another party and utility towards it changed evaluations of other parties in ways not captured by the rest of the model).

$$P(A|B) = \frac{P(A \ \cap B)}{P(B)}$$

For example, we can update our beliefs about the probability that it will snow tomorrow if we are given conditions about geography and time of year: $P(snow|Texas, summer)$ approaches 0 but $P(snow|Minnesota, winter)$ is quite high.

Bayes' Rule follows from the definition of the conditional probability. Since $P(A|B) = \frac{P(A \cap B)}{P(B)}$ but $P(B|A) = \frac{P(A \cap B)}{P(A)}$, which implies $P(A \ \cap B) = P(B|A)P(A)$, substituting yields $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$, which is Bayes' Rule. So, for example, suppose we are interested in the probability, A, that someone will support the Republicans in an election and we know B, whether or not the person registered Republican (which, of course, is not the same, as the voter may have registered years ago and since changed her preferences). Bayes' Rule holds

$$P(supports\ GOP|registered\ GOP) = \frac{P(registers|supports)P(supports)}{P(registers)}$$

If we have information about the prior distribution of GOP support, $P(supports)$; the conditional probability supporters have of registering GOP, $P(registers|supports)$; as well as the probability about registering in the first place, $P(registers)$, then we can make direct inferences about the quantity of interest, which is the probability of supporting Republicans given our knowledge of party registration (the data), $P(supports\ GOP|registered\ GOP)$.

Bayes' Rule generalizes allowing for multiple outcomes (Casella & Berger, 2002, p. 23). If the sample space is partitioned into A_1, A_2, … and B is any set, then for each k = 1, 2…

$$P(A_k|B) = \frac{P(B|A_k)P(A_k)}{\sum_{j=1}^{\infty} P(B|A_j)P(A_j)}$$

So, suppose there were an election in the United Kingdom with only three parties running, Labour, Conservative, and Liberal Democrat, and suppose we knew a voter's vote choice and wanted to update our beliefs about, say, utility towards the Labour party. Then we would have, for example,

$P(Utility_L|Vote) = \frac{P(V|U_L)P(U_L)}{P(V|U_L)P(U_L)+P(V|U_C)P(U_C)+P(V|U_{LD})P(U_{LD})}$, where $P(U_L)$ is the prior distribution of utilities towards Labour, $P(V|U_L)$ is the conditional probability of vote choice given utility towards Labour, and $P(Utility_L|Vote)$ is the posterior probability distribution of utility given the data about voting behavior.

This framework adapts easily to the regression context since the likelihood function is a conditional probability function. The likelihood $f(\boldsymbol{x}|\theta) = \prod_{i=1}^{n} f(x_i|\boldsymbol{\theta})$ is, by definition, the joint probability of the data given that the unknown vector of parameters, $\boldsymbol{\theta}$, is fixed (Casella & Berger, 2002, p. 290). This allows $\boldsymbol{\theta}$ to take the place of A and the likelihood function to take the place of $P(B|A_k)$. Specifically, the posterior distribution of an unknown parameter θ, given the data $\boldsymbol{x}$, is equal to its prior distribution multiplied by the likelihood divided by the probability of the data (the marginal distribution of $\boldsymbol{x}$):

$$\pi(\theta|\boldsymbol{x}) = \frac{f(\boldsymbol{x}|\theta)\pi(\theta)}{m(\boldsymbol{x})}$$

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where $m(\boldsymbol{x}) = \int \pi(\theta) f(\boldsymbol{x}|\theta) d\theta$ (Casella & Berger, 2002, p. 324). Since $m(\boldsymbol{x})$ is just a constant that ensures that the posterior distribution is a valid probability distribution (that integrates to 1), statisticians often stress the proportion $\pi(\theta|\boldsymbol{x}) \propto f(\boldsymbol{x}|\theta)\pi(\theta)$. When there are multiple (say *k*) unknown parameters, as is the case here, $\boldsymbol{\theta}$ follows a multivariate distribution such that $\pi(\boldsymbol{\theta}|\boldsymbol{x}) = \pi(\theta_{\boldsymbol{1}}, \dots, \theta_{\boldsymbol{k}}\,|\boldsymbol{x}) \ \propto f(\boldsymbol{x}|\boldsymbol{\theta})\pi(\boldsymbol{\theta})$ (Jackman, 2009, p. 22).

In the case of hierarchical models, such as the one presented here, the prior distribution is sometimes interpreted as the second (here party) level of the model. This reflects in turn the belief that the (pooled) parameters come from a common distribution. The parameters are *exchangeable* in the sense that, absent other information (data), the probability assignment is invariant to the way that the parties are labeled. Suppose, for example, in the model described here, there are strong class cleavages that are poorly captured. We would expect the variance of the effect of class, $Var(b_{3,j})$, to be quite high—people would either love or hate each and every party, depending on their class statuses. Exchangeability dictates that, absent countervailing data, the variance associated with $b_{3,j}$ would be the same throughout the EU (Jackman, 2009, p. 45). The distribution of the prior parameter θ_j (for example $b_{3,j}$) is then modeled to depend (hierarchically) on some hyperparameter *v:*

$\theta_j|v \sim p(\theta_j|v)$ $\qquad$ $(hierarchical\ model\ for\ \theta_j|v)$

$v \sim p(v)$ $\qquad$ $(prior\ for\ hyperparameter\ v)$

`

In general, hierarchical models are useful for representing complex causal processes as a series of relatively simple relationships, that is, representing them in terms of a series of distributions that would be known if only the value of its parameters (or at least the parameters' distributions) were known.

Modeling the distribution of the prior allows the data to be described as *conditionally exchangeable:* if we did not model the systematic ways in which people's responses to parties differ, the data would not be exchangeable (independently and identically distributed). However, conditioned on the party level parameters, the data can be treated as if exchangeable (and hence at least "partially pooled"). In this way, hierarchical models can account for causal heterogeneity (Jackman, 2009, p. 45). Put differently, despite the heterogeneity introduced by the party valences, λ_{ij}, we can still make inferences about β_1, the general effect of ideological distance.

Chapter Three: Data

This section analyzes party preference in the European Union using the European Election Study (EES) that was taken in conjunction with the 2009 European Parliament elections. This means that this EES studies EU-27: it includes the original 15 member states[6], the 10 countries[7] that joined the EU in 2004, as well as Bulgaria and Romania, which joined in 2007, but not Croatia (which did not join until July 2013).

Even though the smallest parties are not asked about, every respondent is asked about at least four parties (Malta) and as many as 12 (Spain). The dependent variable is not individual attitude but individual affinity towards a particular party. There are 27,069 respondents (N_i). This means there are roughly 1,000 respondents per country and so roughly 1,000 observations per party. The 203 parties $\left(N_j\right)$ in the sample are dispersed in such a way so as to translate into 203,470 observations on the dependent variable $\left(N_{ij}\right)$.

The survey also asks respondents to rate both themselves and each of their country's parties (a) in terms of left and right and (b) in terms of whether EU integration has gone too far (or not far enough). All ratings are done on an 11 point scale (from 0 to 10, inclusive), and these questions are used to measure Euclidean distance. Note that the distance measure is "subjective" in the sense that it captures the respondent's perception of the party's position relative to her own, rather than the party's official stance (or otherwise estimated position). This is appealing in that an individual may "feel like" a party is "too conservative" for her without knowing

[6] Belgium, France, Germany, Italy, Luxembourg, and the Netherlands are the original members that joined in 1958. Ireland, Denmark, and the Netherlands joined in 1973; Greece in 1981; Spain and Portugal in 1986; Austria, Sweden, and Finland in 1995.
[7] Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia.

exactly how the rest of the public would place the party (or her) in terms of left and right. An individual may feel that a party "goes too far" down the road of European integration without knowing the particular official stance that the party happens to take in the election. Parties may also feel an incentive to dissemble their stances in an election, limiting the utility of manifestos. The subjective data used here are, however, limited in that such party placements are something of a "black box"—these estimates offer us a sense of the effects of such perceptions without saying why some people have them while others do not. Though it is beyond the scope of this paper, I think such perceptions of party position are better modeled separately (as a function of official party stance, the individual's political awareness, and so on).

The second level of the model includes demographic variables—*European Identity, Education, Class,* and *Migrant Background*—which are modeled as variables that explain the respondent's affinity for each party above or below the party's baseline level of support. *European Identity* is based on whether the respondent identifies as national only, national and European, European and national, or European only (Q82). *European Identity* is considered as an ordinal measure. This operationalization is consistent with the findings from Mohanty (2012) that viewing such values as a continuum yields stronger predictions than, say, having separate, competing variables for the two.

Missing data is a potential source of bias because, unless the data is missing completely at random, which is rarely the case in the social sciences, it introduces dependencies into what should be an independently and identically distributed sample, thereby limiting the extent to which findings correspond to the population. Missing data can be handled by modeling each missing variable as a parameter to be estimated as part of the Gibbs sampler or through multiple imputation. This paper adopts the latter approach because one of the key explanatory variables—Euclidean distance—depends on four questions (self- and party-placements in terms of left/right and EU integration) which do not enter directly into the final model. I imputed these using random regression and any other variables with missing data, on a country-by-country basis following the technique described by Gelman and Hill (2009, p. 529). Random regression balances the available information and the inherent noise of the data generating process. Rather than directly estimating the missing values, it estimates the parameters of the probability distribution that likely would have generated missing items. Results presented here are based on 1,000 rounds of imputation. For Model 1, variables are centered at their means to facilitate convergence (Gelman & Hill, 2009, p. 415).

The dependent variable is how likely each respondent is to vote for any given party in his country on a Likert scale of 0 to 10.[8] The data are not, however, probabilities in the sense that respondents are not required to make their responses sum to 1 (or any other constant), so the data do not need to be treated as "compositional data."[9]

Zero is—by far—the modal response for the dependent variable (as Figure 3 shows). This makes sense because presumably voters on the far left do not seriously consider parties on the far right, centrist voters do not seriously consider extreme parties, and so on. Approximately 80% of those surveyed responded zero for at least

[8] In the United Kingdom, the question was put: "We have a number of parties in Britain each of which would like to get your vote. How probable is it that you will ever vote for the following parties? Please specify your views on a scale where 0 means 'not at all probable' and 10 means 'very probable'."

[9] For an introduction to this topic, see Aitchison (1986).

one party. Despite the relatively large number of categories, the distribution of responses still shows the unevenness that marks categorical—rather than continuous—data, which is reason to think that an ordinal response model may be appropriate.

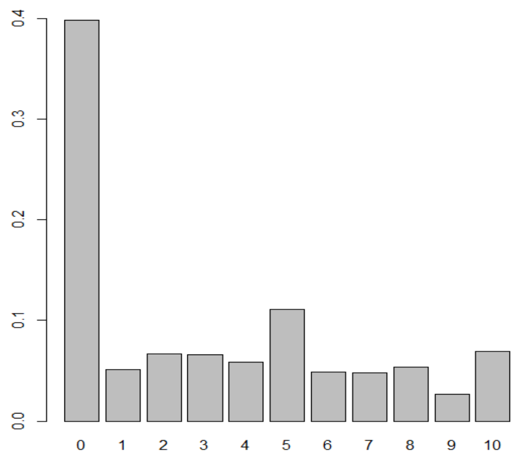

Figure 3: Histogram of Responses on Dependent Variable.

Zero response is not distributed independently of party. As Figure 4 shows, some parties have almost no zeros, while others have almost all. One possible reason to think that it is unnecessary to model zero inflation is that the excess zeros will simply be absorbed into the party intercept. To foreshadow, the Model 1 estimates do suggest that this adjustment happens to some extent but not strongly (the correlation between proportion of zeros at the party level and the party intercept is -0.08). This makes sense in that hierarchical estimates are sometimes called "shrinkage estimators" because they tend to shrink extreme estimates back towards the mean. So, if there is some small party that 80% of voters say that they would never vote for, the hierarchical model will still tend to shrink the party intercept back towards the mean.

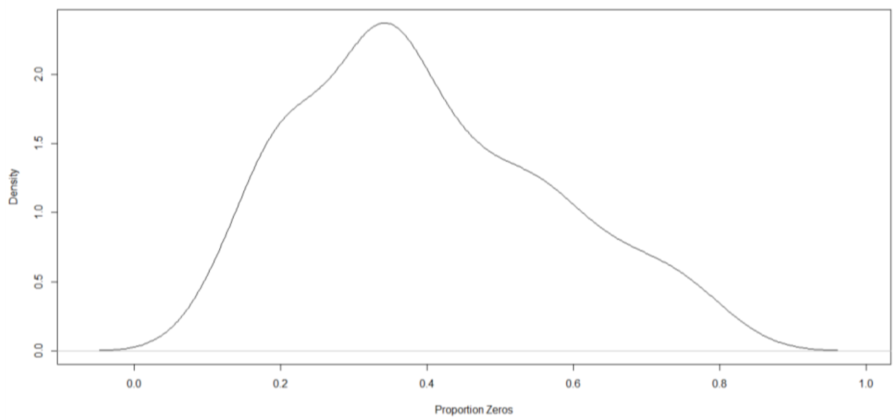

Figure 4: Zero Response (Density of Proportions by Party).

Chapter Four: Markov Chain Monte Carlo Estimation

Markov Chain Monte Carlo (MCMC) is extremely useful for performing integrations and maximizations that are either analytically impossible or computationally infeasible to perform directly. The Monte Carlo principle is that "anything we want to know about a random variable θ can be learned from sampling many times from $f(\theta)$, the density of θ" (Jackman, 2009, p. 133). Markov Chains are a particular kind of sequential probability structure in which the distribution of the present value depends, at most, on the random variable which immediately precedes it. Expressed formally, for the sequence of random variables $X_1, X_{2,}$ …. to be a Markov chain,

$$P(X_{k+1} \epsilon A | X_1, \dots, X_k) = P(X_{k+1} \epsilon A | X_k)$$

These distributions are sometimes called "memoryless" because $X_1, \dots, X_{k-1}$ contain no additional information about the distribution of X_{k+1}. Under certain regularity conditions that are often met when doing statistical inference, a generalization of the Law of Large Numbers, known as Ergodic theorem, holds that as $n \to \infty$,

$$\frac{1}{n}\sum_{1}^{n} h(X_i) \to Eh(X)$$

provided the expectation exists (Casella & Berger, 2002, p. 270). So, for example, if $h(X_i) = X_i$ an $\mathrm{g}(X_i) = X_i^2$, then, as $n \to \infty$, $\frac{1}{n}\sum_1^n g(X_i) - \left(\frac{1}{n}\sum_1^n h(X_i)\right)^2 \to EX^2 - (EX)^2 = Var\ X$, which is not a sample quantity but the second central population moment of the distribution. The Monte Carlo principle cannot be used to make inferences about the posterior distribution of θ when the distribution is unknown (which is often the case for posteriors). However, it is possible to start with certain known distributions and to transition to the posterior distribution using Markov Chains. Gibbs samplers are a popular type of Markov Chain Monte Carlo that sample the conditional distributions of a model's unknown parameters in order to completely characterize their posterior distributions (Jackman, 2009, p. 214). And, since Markov Chains are memoryless, once the sampler has converged on the posterior, it doesn't matter where it started. Once the distribution has converged, inferences can be made simply by specifying the function $h(X_i)$ and applying it to the sequence of random variables generated by the sample. So, if we are interested in the chance that the target variable is positive, we can find out what that chance is by letting $h(X_i) = I_{(0,\infty)}(X_i)$, an indicator function that takes the value 1 if $X_i > 0$ and 0 otherwise, since $\frac{1}{n}\sum_1^n h(X_i)$ will equal the appropriate proportion.[10]

I estimate the model using *MCMChregress*.[11] The function implements the block Gibbs sampler found in Algorithm 2 of Chib and Carlin (1999). This approach uses standard, conjugate priors, which means that the posterior distribution belongs

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10 This can be done easily with the built in logical functions in *R*. If we want to know the probability that the first parameter is positive, this can be done with the command *mean(my.model.output$mcmc[,1] > 0)* since the comparator will return a Boolean vector which *R* averages as if it were a vector of zeros and ones.

11 *MCMChregress* is found in the *R* package *MCMCpack* (Martin, Quinn, & Park, 2013). I recommend this software, which is implemented in C++, over *WinBUGS* for both speed and ease of use (as it doesn't require a separate file programming the model and is called much like other regression functions in *R*). *WinBUGS*, however, still has greater flexibility in terms of model design (as *MCMChregress* can handle varying intercepts but cannot handle non-nested models, models with multiple levels, and so on).

to the same family as the prior (Casella & Berger, 2002, p. 325). Specifically, the prior distribution of $\boldsymbol{\beta}$ is multivariate normal. σ_u^2 follows an $Inverse\ Gamma\left(v, \frac{1}{\delta}\right)$ prior distribution. The (hyper)prior distribution of D, the variance covariance matrix of the party level effects, is $Inverse\ Wishart(r, rR)$, where r, the degrees of freedom, is the length of $\boldsymbol{b}$ and $\boldsymbol{R}$ is a square scale matrix.

Block Gibbs samplers are a type of Gibbs sampler that updates certain parameters all at once so as to reduce serial correlation. In this case, the slope coefficients for both levels of the model, $\boldsymbol{b}$ and $\boldsymbol{\beta}$, are updated at the same time (Chib & Carlin, 1999). Chib and Carlin show that the block update is possible since the conditional distribution of $\boldsymbol{\beta}$ does not depend on $\boldsymbol{b}$, so once y, σ_u^2, and D are updated, $\boldsymbol{\beta}$ and $\boldsymbol{b}$ can both be updated before moving on to the other parameters.

Assessing Convergence

The greatest danger when using MCMC is that one might draw inferences from a chain that has not converged yet on its target (the posterior distribution of the model given the data) (Kass, Carlin, Gelman, & Neal, 1998). To assess convergence, I took several steps.

I estimated three chains, each of which was given different starting values. *MCMCpack* does not permit starting values for group level predictors since these are sampled based on the first round of samples. I used OLS estimates for the first chain (the software default) and drew from diffuse random normal distributions for the next two. (*MCMCpack* generally defaults to diffuse priors.) These starting values do not have any influence on the final chain, however, as the first 1,000 draws are discarded as "burn in."

Autocorrelation is a problem for MCMC methods in general and in particular for multilevel models. This is because the group-level correlation often leads to autocorrelation in the sample chains. Autocorrelation reduces the amount of unique information contained in each sample. It is best to have several thousand independent samples for each parameter (or the equivalent) before making inferences (Jackman, 2009, p. 251ff). I took 100,000 draws (after the initial burn-in of 1,000 draws) for each chain and thinned that sample by a factor of 20 (retaining only 5,000 samples per unknown parameter). Thinning does not increase effective sample size but reduces storage requirements (which reduces the computational burden of posterior calculations).[12]

For each chain, I analyzed the Geweke diagnostic[13] to confirm that the first tenth of the samples (for each parameter) have the same mean as the last half. The test statistics should—and do—resemble a standard normal: for each chain, the mean is -0.021 and the standard deviation is 0.95. Next, I analyzed the effective sample size, which is a measure that discounts the nominal sample size based on the degree of autocorrelation. Even after being thinned by a factor of 20, a small amount

[12] I may have thinned more than is necessary but not by much—based on early model specifications, a thinning factor of *at least* 16 is necessary (at this number of iterations) to maintain a sufficiently large effective size for all parameters (while ultimately storing only 5,000 samples).

[13] I did so using the *gelman.diag(),geweke.diag()* and *n.effective()* functions, all of which are found in the *coda* package in *R* (Plummer, Best, Cowles, Vines, Sarkar, & Almond, 2012).

of autocorrelation was still present, but there was fortunately a sufficient sample for each parameter: there were a minimum of 3,600 independent samples with a (much higher) mean of 4,995 (all figures per parameter per chain).

Next, I inspected Gelman and Rubin's Convergence Diagnostic, $\hat{R}$, which is used to determine the level of similarity multiple chains have to one another. The diagnostic works in a fashion similar to one-factor ANOVA—loosely speaking, by analyzing the ratio of within-chain to between-chain variation. It converts the variances and covariances of the chains into a single score that approaches 1 (from some larger number) as the chains near convergence. This test is more demanding than Geweke's because it is much more likely that two groups happen to have the same mean than that they covary in the same fashion—after all, those computations involve mean comparisons. $\hat{R}$ should be less than 1.1 or 1.2 for all parameters (Gelman, Carlin, Stern, & Rubin, 2004, pp. 294-8). In fact, $\hat{R}$ is 1 for all 1,044 parameters in the model, suggesting complete convergence (which explains why the other test statistics are identical).

	Geweke Test Statistics		Number of Effective Samples		$\hat{\boldsymbol{R}}$
	Mean	*SD*	*Min*	*Mean*	*Max*
Chain 1	-0.021	0.951	3,600	4,995	
Chain 2	-0.021	0.951	3,600	4,995	
Chain 3	-0.021	0.951	3,600	4,995	
(All chains)					1

Table 1: Convergence Measures

Finally, the amount of error associated with the Markov Chain Monte Carlo estimation is quite low: both naïve and time-series standard errors are uniformly less than 0.005. In sum, there is good reason to believe that the sampler converged. The target, however, unfortunately does not closely resemble the distribution of the data (as can be seen in Figure 5 below). The large number of zeros in the data shifts the posterior to the left, which means that high levels of support are not predicted as often as they should be: roughly 24.7% of the data are above 5, whereas only 14.1% of the posterior predictions are. Worse, 15.0% percent of the data are greater than 7, but only 0.5% of the predictions are. Similarly, certain categories (1-4) are predicted to have far higher levels than is likely.

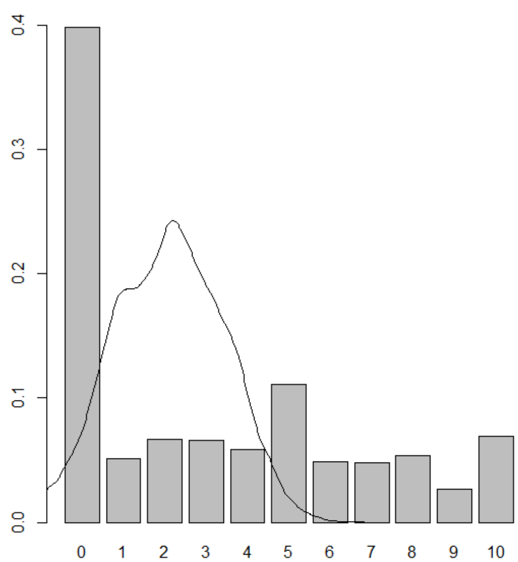

Figure 5: Density of Model 1 Predictions vis-à-vis Observations.

Chapter Five: Results

The posterior distribution contains a wealth of information. This section provides a brief overview of the results and illustrations of some types of claims that can be evaluated with the posterior. The model is somewhat difficult to summarize because it has 1,044 unknown parameters: overall intercept, effect of distance, (203 parties) * (party intercept + coefficients for 4 sociodemographic variables), and variance covariance parameters. Bayes factors provide a method for deciding whether or not to include parameters that is quite similar to a Likelihood Ratio test (Jackman, 2009, p. 37). I do not adopt this approach since it is entirely possible that a particular sociodemographic variable would influence the appeal of some parties but not others (or in some places but not in others) and so be substantively important without providing definite evidence that the variable must be included. The model should be able to identify when a variable is important and when it is not (and perhaps shed some light on how the model might be improved if a variable is only important in a subset of cases).

Figure 6 provides an example of how the model estimates can be summarized graphically by focusing on the credible intervals of a subset of the parameters of interest. In this case, 95% Highest Posterior Densities[14] (HPDs),

[14] Credible intervals differ from confidence intervals since in the former case the parameter is considered a random variable. For any given section of the parameter's support, there is a certain chance α (implied by the cumulative proportion of the posterior distribution which is found in that region) that the parameter would take that value. For unimodal posteriors, such as the one investigated here, the HPD can be written: $\{\theta: \pi(\theta|\boldsymbol{x}) \geq k = \pi(\theta_{Lower}|\boldsymbol{x}) = \pi\big(\theta_{Upper}\big|\boldsymbol{x}\big)\}$ where
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which correspond to roughly two standard deviations on either side of the point estimate, are provided for Germany.

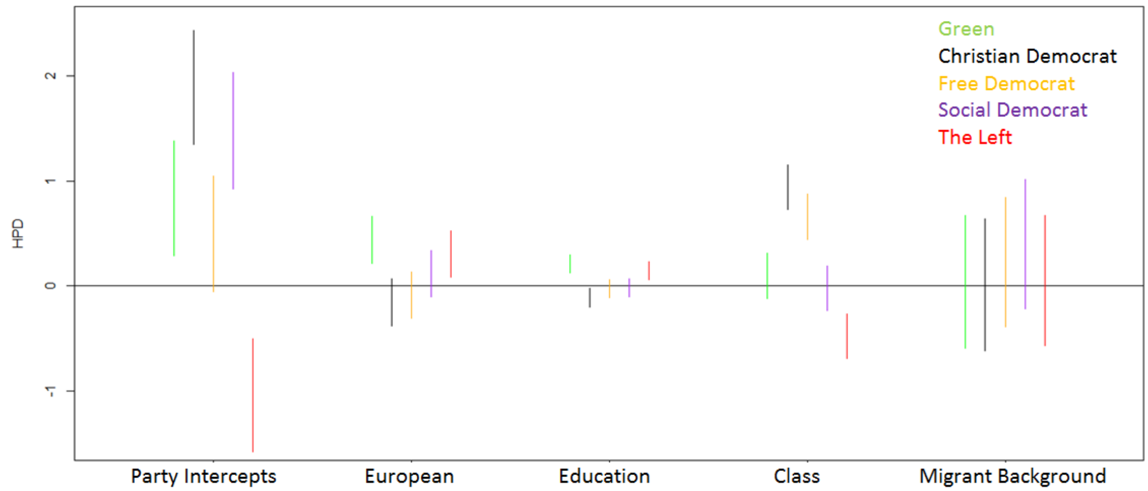

Figure 6: Highest Posterior Densities (95%) for Party-Level Effects in Germany

The rank order of the party intercepts λ_j—Christian Democrats (with Christian Socialists) placed first, followed by Social Democrats (SPD), followed by Greens (with Alliance '90), followed by Free Democrat (FDP), followed by a new political party called "the Left" —happens to correspond exactly to that of the election results. The estimates show that the CDU and their longtime coalition partners, the FDP, are more appealing to wealthy voters, while the Left has the clearest working class appeal. Despite its origins with union politics, the SDP moved towards the center under the leadership of President Gerhard Shroeder, so it is perhaps unsurprising that class has relatively little effect on support for the SDP or for the

$\int_{\theta_{Lower}}^{\theta_{Upper}} \pi(\theta|\boldsymbol{x})d\theta = 1 - \alpha$. (Casella and Berger 2002, 441, 447-8; Jackman 2009, 26). Here, the posterior is unimodal, but the data is not, so the credible intervals need to be taken with a large grain of salt.
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Green party, with which it often partners. The results suggest that voters with European identities favor parties on the left (SDP, Green, and the Left) while those with nationalist identities favor those on the right (CDU, FDP) but that these party level effects are relatively small. This suggests in Germany, perhaps, that concerns about Europe are well captured as a matter of policy distance and that it may not be necessary to model national vs. European identity in addition to a spatial distance measure which includes integration policy. The results also suggest that knowing the educational background of a voter adds little information about her party preference. Those with a migrant background find the Social Democrats the most appealing, but the effects of migrant background are particularly noisy (a trend discussed further below).

Below, I present a succinct summary of the model. The summary includes point estimates for the parameters of the ground level of the model, variance covariance terms, and measures of fit. Standard deviations of the posterior (somewhat analogous to standard errors) are also included. As point estimates, as is standard, I include the mean of the posterior distribution for each parameter since it minimizes expected squared error loss (Jackman 2009, 24, Casella and Berger 2002, 353). Since distance is on a 0 to 200 scale, which is somewhat difficult to interpret, I also provide estimates of the effect per standard deviation of distance and distance's maximum. As an additional measure of uncertainty, I include the proportion of the posterior distribution that has the opposite sign of the point prediction. This measure can be thought of as a Bayesian analogue to a one-sided p-value in the classical framework (and so is denoted p_{Bayes}).[15]

For party level intercept and coefficients, I present the mean of several quantities of interest (for all 203 parties) for both the effects and associated uncertainty. In order to give a sense of the magnitudes, I focus on absolute estimates (since party level effects have mean zero). For example, some parties may be popular with high income (translating into positive party-level coefficients) and others not (translating into negative coefficients), but simply averaging across all parties would make it look as if class had no effect on support for any party. Estimates are given for a standard deviation of the relevant $\boldsymbol{W}$ variable and for the difference between the sample maximum and minimum value of $\boldsymbol{W}$.

Deviance Information Criteria (DIC) is an analogue of Aikaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) that is used to evaluate multilevel models. Those measures penalize for including too many parameters; they are not appropriate for multilevel models because in multilevel models the number of parameters in the model varies widely based on which parameters are pooled (Gelman & Hill, 2009, pp. 525-7). Since DIC is mainly useful for model comparison, which is not done here for models of this class, I also include, as a pseudo-R^2, the squared correlation between the predictions and the observations.

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15 The difference is that a classical p-value measures the odds of observing data that is at least as extreme as the data in hand, given the null hypothesis, whereas the Bayesian paradigm treats the parameter of interests as a variable and the observed data as fixed.

The squared correlation is one readily calculable definition of the classical R^2 that is asymptotically equivalent to the others (maximization of model sum of squares, minimization of residual sum of squares) (Tjur, 2008). Considering the model predicts party preferences in 27 countries with only seven explanatory variables, counting intercepts, the correlation is fairly robust at 0.4995. Full results (party-by-party point estimates with 95% HPDs) are provided in the Appendix.

Evaluations of Parties $N_{ij} = 203{,}470$		*Effect*			*Uncertainty*	
	Support	*Estimate (Mean)*	*per SD of X*	*Maximal*	*Standard Deviation of Estimate*	p_{Bayes}
Overall Intercept	{1}	0.779	n/a	n/a	0.255	0.001
Squared Euclidean Distance	[0, 200]	-0.023	-0.801	-4.78	0.001	0

Party Level Effects $N_j = 203$		*Mean Absolute Effect*		*Mean Uncertainty*	
	Support	*per SD of X*	*Maximal*	*SD*	p_{Bayes}
Party Intercept	{0, 1}	n/a	1.01	0.278	0.058
European	[-0.707, 2.293]	0.157	0.653	0.129	0.145
Education	[-5.623, 13.377]	0.289	1.54	0.036	0.106
Class	[-2.253, 2.747]	0.242	1.286	0.109	0.116
Migrant	[-0.0736, 0.926]	0.1	0.464	0.427	0.214

Variance-Covariance Matrix	*Party Intercept*	*European*	*Education*	*Class*	*Migrant*
Party Intercept	1.612				
European	-0.036	0.122			
Education	0.034	0.012	0.038		
Class	0.063	-0.002	-0.002	0.154	
Migrant	-0.054	0.039	0.004	-0.098	0.641

N Respondents	27,069
$\widehat{\sigma_u^2}$	8.488
Deviance	1,012,577.58
Pseudo-R^2	0.250

Table 2: Model Summary

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As hypothesized, greater spatial distances correspond to lower party utilities. (In fact, none of the posterior has the opposite sign.) The slope coefficient is -0.0239 with a 95% highest posterior density (HPD) interval of (-0.025, -0.022). Since placements are initially on a 0 to 10 scale, the maximum possible distance is $\sqrt{200}$ (making the maximum possible squared distance, to which the slope coefficient corresponds, 200). At this maximal distance (which is observed in sample), holding other things equal, a person would be predicted to respond 4.78 ± 0.2 units lower than someone at zero distance would.

As hypothesized, party valences are important. The party intercepts, $\widehat{\lambda_J}$, have a mean absolute effect of about 1 unit, suggesting that roughly 10% of voters' evaluations, averaged across parties, are explained by factors other than ideology and sociodemographic affinities. This may not seem like much but, bear in mind, this is actually a fairly hard test for party valences: since the European Parliament is an historically weak institution, EP elections present an ideal opportunity to vote for the ideologically preferred (as opposed to politically viable) party.

Sociodemographic variables, taken collectively, are very important: voters at opposite ends of all of the spectrums evaluate parties almost as differently as voters at the complete opposite end of the ideological space. Suppose a party appeals mainly to wealthy, educated, migrants with predominantly European identities, which describes the elites often called "Eurostars" (Risse, 2010). A working class native (with a matching nationalist identity) would be expected to evaluate that party roughly 4 units differently than the “Eurostar” (even if they described themselves the same ideologically).

There is clearly more uncertainty associated with *migrant background* than with the other sociodemographic variables. Of course, to some extent this may simply reflect the fact that only 10% of respondents report that they or their parents were born abroad. And this isn’t necessarily cause for alarm: not all parties take stances of immigration. Further, not all countries in the European Union experience high levels of immigration; large immigrant populations are still concentrated in the Western, wealthier member states.

Suppose one wished to evaluate this claim by comparing the degree of uncertainty in the original 15 member states (EU-15) with that found in the new member states. One way to see that this explanation does not hold is to partition the posterior density into EU-15 and new member states:

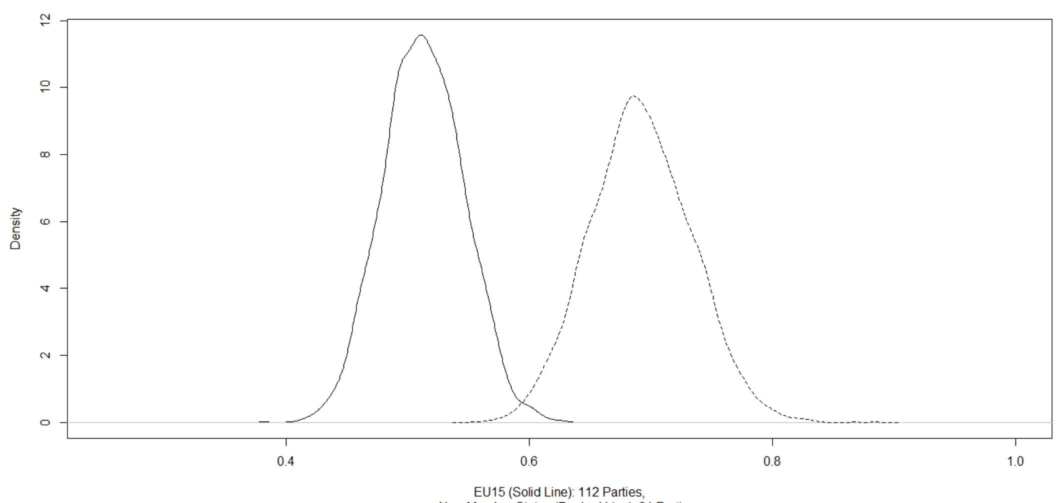

Figure 7: Mean Absolute Effect of Migrant Background, EU-15 vs. New Member States

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Doing so reveals that there is actually a larger absolute effect of migrant background in the new member states. The model predicts an especially large effect of migrant background in Estonia and Latvia, and, to some extent, in Lithuania (all Baltic states with land borders to the outside of the EU).

Another explanation may lie with type of party: immigrants tend to gravitate towards center-left parties in Europe in part because of the hostility of parties on the right and in part because of social policy (Messina, 2007). One way to evaluate this claim is to average posterior samples according to the party group in which the party sits in the European Parliament. (This time there is no need to evaluate absolute effects since we would expect parties which affiliate with one another to either be more appealing to migrants or natives in general.) Here there are clear findings consistent with the literature: as Table 3 below shows, other things being equal, there is an overwhelming chance that migrants find center or left parties more appealing while natives are more attracted to conservative parties.

Party Group	*Parties*	*Mean Effect of Migrant Background*	*Posterior Probability of Appealing More to Migrants than to Natives*
European People's Party (EPP)	40	-0.238	0.1%
Party of European Socialists (PES)	30	0.142	95.7%
Greens-European Free Alliance (Greens-EFA)	18	0.441	100%
Alliance of Liberal Democrats (ALDE)	35	0.088	87.6%
European United Left-Nordic Green Left (EUL-NGL)	13	0.332	99.6%
European Conservatives and Reformists (ECR)	7	-0.072	33.6%
Europe of Freedom and Democracy (EFD)	9	-0.021	44.1%
(Not Affiliated)	51	0.0001	49.7%

Table 3: Migrant vs. Native (Posterior) Party Group Preferences

So, when viewed this way, the effects are clear but not particularly large in magnitude. This could offer some explanation as to why there is so much uncertainty at the party (as opposed to party group) level.

A Comparison with Single-level Ordinal Regression

This section uses maximum likelihood estimation as the method for assessing the data and will use ordinal probit and logit to build models. Ordinal probit or logit is appropriate when there are multiple, discrete categories where there is clear rank—for example, whether discrimination is "very widespread," "fairly widespread," "fairly rare," or "very rare"—but where the difference between the categories cannot be assumed to be uniform (Liao, 1994, p. 37ff). Rather than assuming that each choice represents a scalar value, we assume that there is a latent variable (y*) at work with its own probability distribution—typically, Gaussian or logistic—and that each choice corresponds to a portion of that pdf. This means that the responses must be transformed by a link function before they can be treated linearly. We further assume the dependent variable y is explained by a structural component and a symmetrically distributed error term ε, such that:

$$y^* = \sum_1^k \boldsymbol{\beta}_k \boldsymbol{x}_k + \varepsilon$$

In the above equation, x represents a vector of (fixed) independent, explanatory variables (and β the corresponding vector of coefficients).

We assume that there is a range of beliefs that corresponds to each discrete choice and use ordinal regression, logit or probit, to estimate the location of the boundaries between discrete choices. μ represents an unknown threshold parameter that separates the j categories; this means:

$$\begin{aligned}
y &= 1 \text{ if } y^* \leq \mu_1 (=0) \\
&= 2 \text{ if } \mu_1 \leq y^* \leq \mu_2 \\
&= 3 \text{ if } \mu_2 \leq y^* \leq \mu_3 \\
&: \\
&: \\
&= J \text{ if } \mu_{j-1} \leq y^*
\end{aligned}$$

If F is the cumulative distribution function of Y, then:

$$Prob(y = j) = F(\mu_j - \textstyle\sum_1^k \boldsymbol{\beta}_k \boldsymbol{x}_k) - F(\mu_{j-1} - \sum_1^k \boldsymbol{\beta}_k \boldsymbol{x}_k)$$

I adapt the hierarchical model presented earlier to a single level model on the intuition that effects of the higher level of the model can be viewed as conditioning the outcome of effects at the lower level. Below, Table 4 presents maximum likelihood estimates of three ordered probit models.[16] Model 2 includes only spatial distance. Model 4 models interaction between distance and each of the

[16] Estimated by *polr()* in the *MASS* library in *R* (Ripley, Venables, Bates, Hornik, Albrecht, & Firth, 2013).

sociodemographics. Model 3 serves mainly to facilitate comparison, as it includes the sociodemographics, but without interactions.

		Model 2	Model 3	Model 4
	Squared Euclidean Distance	-0.022 (0.0002, -144.2)	-0.022 (0.0002, -144.557)	-0.023 (0.0002, -144.768)
	European Identity		0.052 (0.0059, 8.733)	0.12 (0.0081, 14.756)
	Education		-0.021 (0.0012, -17.267)	-0.001 (0.0017, -0.758)
	Class		0.104 (0.0047, 22.333)	0.172 (0.0064, 26.884)
	Migrant		0.095 (0.0189, 5.041)	-0.051 (0.0257, -1.996)
	$Distance^2$ x European			-0.003 (0.0002, -12.043)
	$Distance^2$ x Education			-0.001 (0, -17.113)
	$Distance^2$ x Class			-0.003 (0.0002, -15.415)
	$Distance^2$ x Migrant			0.006 (0.0007, 8.174)
Intercepts:	0|1	-1.1068	-1.1118	-1.115
	1|2	-0.8701	-0.8745	-0.877
	2|3	-0.5701	-0.5734	-0.575
	3|4	-0.2738	-0.276	-0.276
	4|5	-0.0026	-0.0037	-0.003
	5|6	0.5636	0.5644	0.568
	6|7	0.8618	0.8635	0.868
	7|8	1.2124	1.2149	1.221
	8|9	1.733	1.7361	1.743
	9|10	2.0927	2.096	2.104
	Residual Deviance	796,885.10	796,136.97	794,986.05
	AIC	796,907.10	796,907.10	795,024.05
	N_{ij}	203,470	203,470	203,470
	Pseudo-R^2	(non-finite)	(non-finite)	0.669

Table 4: Maximum Likelihood Estimates for Ordered Probit Models.

Standard Errors and t-values in parentheses. SEs and t-values omitted for intercepts, but, with the exception of the boundary 4|5, which is not significant because the latent variable is centered at zero, all boundaries for all models are highly significant.

There are some changes to the model specifications worth noting. Models 3 and 4 allow for the possibility that sociodemographics may have main effects.[17] This means that these coefficients may be interpreted to reflect the extent to which a group receives higher utility on average from all parties in their country than other groups. (This, presumably, would translate into higher voter turnout for that group). Consistent with theories that the European voters often turn to radical right wing populism because of alienation with the mainstream political system (Givens, 2005; Holmes, 2009; Simmons, 1996), the estimates do suggest that parties are generally more appealing to Europeanized (economic) elites than to working class nationalists.

As Figure 8 shows, all three accurately reproduce the pattern of observed responses. This is a function, however, of the fact that ordinal categorical regression is equivalent to a series of binary regressions and so this is not sufficient to show accurate prediction. For each observation, I use the category with the highest probability as the prediction. Based on the same pseudo-R^2 of squared correlation between the predicted and the observed, Model 4 (and only Model 4) shows clear improvement over Model 1: fit improves more than twofold from 0.25 to 0.669.

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[17] Since interactions between x_1 and x_2 are typically expressed by the regression equation $b_1x_1 + b_2x_2 + b_3x_1x_2$ so that (focusing on the structural equation) the marginal effects (the partial derivatives) reflect both x variables, the model does allow for the possibility of main effects (b_1 and b_2) of the sociodemographics.
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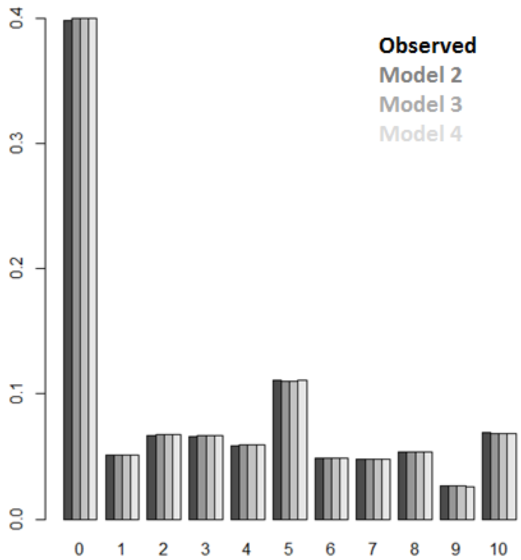

Figure 8: Probability Mass by Response Category

Interactions are notoriously difficult to analyze for generalized linear models because the nonlinear relationship between the structural equation and the data implies a certain amount of interaction whether it is modeled or not (Berry, DeMeritt, & Esarey, 2010). Berry, DeMeritt, and Esarey recommend evaluating likelihood ratio tests to see whether models that include a product term for interactions improve over ones that do not and assessing the substantive importance of the interaction. In this case, all four LR tests were highly significant ($p < 0.0001$). Much more importantly, only Model 4, which includes the interactions, is able to make accurate predictions. In fact, it is not possible to calculate the pseudo-R^2 for Models 2 and 3 because the predicted has a standard deviation of zero. Models 2 and 3 predict that every single respondent is most likely to respond zero, which is to say that it cannot distinguish individual attitudes towards particular parties from the modal response. Modeling the interaction between sociodemographics and distance does shift the interpretation away somewhat from the idea advanced at the outset of this paper (namely, that different parties appeal more to the interests certain groups) and towards the related notion that ideology means different things in different social milieus.

Chapter Six: Discussion

This paper has modeled support for political parties in the European Union beginning with the intuition that voters support ideologically proximate parties with two different approaches. Broadly, the findings here support the argument that there is a European "public sphere" (Risse, 2010) and that political ideology works in similar ways in the EU (Gschwend, Lo, & Proksch, 2012). This is not to say that there are no important differences across the EU, but rather that many of them can be explained by way of reference to characteristics of individuals or parties (as opposed to modeling countries as if they were explanatory factors).

Both approaches account for individual heterogeneity arising from sociodemographic circumstance. Model 1, the hierarchical model, provides strong evidence that it is important to model party competence: for 203 different political parties, an average of over 94% of the posterior density suggested that the party intercept is not zero. Despite the large number of response categories, the dependent variable is clearly not normally distributed because of the large number of zeros. The ability of Model 1 to reproduce the data generating process suffers accordingly.

Model 4 shows that party preference can be modeled parsimoniously by way of an interaction of ideology and sociodemographics. The interactions may not be necessary in the single country context, but Model 2 shows that ideology alone is insufficient is the multinational context. Put differently, the sociodemographics perform something of a matching function in the model which suffices to make ideology commensurate across borders. For example, a working class person may interpret “left” more along the lines of social democracy whereas an elite may interpret “left” more along the lines of cosmopolitanism or environmentalism (and such trends seem to be consistent enough to overcome national idiosyncrasies).

Zero inflated models are common with count data, but have only recently been adapted to ordered categorical models (Harris & Zhao, 2007; Gurmu & Dagne, 2012; Bagozzi & Mukherjee, 2012). They are a particular type of mixture distribution where a single observed outcome actually reflects more than one data generating processes. In this case, it might be helpful to model zero responses, in order to distinguish voters who would never consider supporting a party from those consider how likely they are to support it.[18] However, absent a theory as to which variables affect which latent distribution, this simply doubles the number of parameters to be estimated, which may cause more problems than initial the violation of the Parallel Regression Assumption that zero inflation entails (particularly in the hierarchical context). Model 4 suggests that a reasonably well

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[18] According to Harris and Zhao (2007), if **x** is a set of variables determining whether to consider a party and **z** is a set of variables which is explains the extent of that support, and there are J categories, then

$$\Pr(y) = \begin{cases} \Pr(y = 0|\boldsymbol{z}, \boldsymbol{x}) = [1 - \phi(\boldsymbol{x}'\boldsymbol{\beta})] + \phi(\boldsymbol{x}'\boldsymbol{\beta})\phi(-\boldsymbol{z}'\boldsymbol{\gamma}) \\ \Pr(y = j|\boldsymbol{z}, \boldsymbol{x}) = \phi(\boldsymbol{x}'\boldsymbol{\beta})\left[\phi\left(\mu_j - \boldsymbol{z}'\boldsymbol{\gamma}\right) - \phi\left(\mu_{j-1} - \boldsymbol{z}'\boldsymbol{\gamma}\right)\right] \\ \Pr(y = J|\boldsymbol{z}, \boldsymbol{x}) = \phi(\boldsymbol{x}'\boldsymbol{\beta})\left[1 - \phi\left(\mu_{J-1} - \boldsymbol{z}'\boldsymbol{\gamma}\right)\right] \end{cases}$$

This violates the Parallel Regression Assumption that explanatory variables have homogenous effects across categories (that is, the latent boundaries imply different intercepts, but not different slopes) (Liao 1994) because the effect of **z** is mediated by the effect of **x** in different ways, depending on the response category.

specified ordered probit model can perform well even when the proportion of zeros is high.

The weakness of Model 4 is that it is not grounded as tightly in spatial theory. The inclusion of different combinations of exogenous variables makes it difficult to assess the behavior of certain quantities of interest like the probability each party has maximized its vote share (Nash equilibriums).

One seemingly natural extension would be to combine the best of both models and to fit a mixed effects model with an ordered categorical dependent variable. However, Bayesian ordered probit models are already notoriously slow to converge because of the difficulty of estimating the boundaries between latent categories (Jackman 2009, 401). In this case, a mere four sociodemographic variables translates into 812 party level parameters, which would seem to pose a serious challenge to samplers seeking to distinguish group effects from latent boundaries. Other options exist: *glmer()* in the *R* package *lme4* can be used to estimate a series of hierarchical binary models via Restricted Maximum Likelihood and Greene and Henser (2009) propose a modeling the latent boundaries with structural hierarchical equations, but both of these approaches would seem difficult to interpret (particularly the latter).

All of this puts a very large premium on the accurate modeling of ideology. If ideology can be modeled as a distance term which is properly weighted to reflect the different concerns that different groups have, then the model can be simplified tremendously to one where only the intercepts vary by party (to reflect competence). Jackman (2009, 410) shows how this can be implemented with an ordinal dependent variable; for weighted Euclidean distance, see (Lin, Enelow, & Dorussen, 1999; Hinich & Munger, 1997). To some extent, the strategies can be mixed and matched: if, for example, a researcher feels confident about modeling ideology for several groups (such as class) but not others (such as migrant background), then the former set can be built into the measurement of ideology while the latter can be modeled as having a group level effect. This would give a parsimonious representation of party support while allowing for detailed, party-by-party, breakdown of public support according to variables of interest.

Appendix

This table provides point estimates for party intercepts and effects of each sociodemographic variable on support for each party (based on Model 1). Since party names have been shortened considerably for space, European Election Studies codes are listed beneath each party name. Credible intervals (95% HPDs) are provided below each parameter estimate.

	Party	Intercept	European Identity	Education	Class	Migrant Background
Austria	Future	-1.16	-0.367	-0.035	-0.051	0.013
	1040700	(-1.696, -0.616)	(-0.606, -0.112)	(-0.105, 0.034)	(-0.29, 0.177)	(-0.639, 0.713)
	People's	2.046	0.167	-0.003	0.434	-0.22
	1040520	(1.498, 2.564)	(-0.084, 0.402)	(-0.074, 0.066)	(0.196, 0.668)	(-0.883, 0.466)
	Communist	-2.144	0.247	0.071	-0.14	0.172
	1040220	(-2.665, -1.616)	(0.003, 0.484)	(0, 0.142)	(-0.37, 0.098)	(-0.469, 0.845)
	Freedom	-0.522	-0.566	-0.173	0.113	-0.096
	1040720	(-1.047, 0)	(-0.81, -0.319)	(-0.244, -0.107)	(-0.118, 0.35)	(-0.759, 0.591)
	Martin's List	-0.491	-0.213	-0.163	-0.036	0.181
	1040951	(-1.02, 0.048)	(-0.439, 0.041)	(-0.232, -0.092)	(-0.267, 0.195)	(-0.503, 0.848)
	Social Democrat	1.659	-0.125	-0.04	-0.165	0.744
	1040320	(1.091, 2.169)	(-0.372, 0.122)	(-0.113, 0.027)	(-0.392, 0.075)	(0.059, 1.393)
	Greens	0.501	0.743	0.289	0.042	-0.287
	1040110	(-0.022, 1.046)	(0.491, 0.988)	(0.222, 0.361)	(-0.185, 0.295)	(-0.966, 0.349)
	Young Liberal	-1.803	0.206	0.017	-0.045	0.147
	1040422	(-2.323, -1.267)	(-0.041, 0.445)	(-0.055, 0.088)	(-0.278, 0.187)	(-0.512, 0.834)
Belgium	Christian Democrat & Flemish	1.405	0.171	-0.083	0.382	0.26
	1056521	(0.898, 1.961)	(-0.063, 0.388)	(-0.148, -0.02)	(0.171, 0.608)	(-0.361, 0.852)
	Flemish Interest	-0.855	-0.297	-0.098	0.088	-0.589
	1056711	(-1.364, -0.295)	(-0.53, -0.071)	(-0.166, -0.036)	(-0.127, 0.31)	(-1.195, 0.047)
	Flemish Liberals & Democrats	0.588	0.097	0.057	0.335	-0.444
	1056421	(0.057, 1.116)	(-0.121, 0.34)	(-0.006, 0.122)	(0.13, 0.566)	(-1.056, 0.134)
	Green!	1.25	0.28	0.198	-0.185	0.614
	1056112	(0.709, 1.762)	(0.054, 0.512)	(0.135, 0.262)	(-0.394, 0.036)	(-0.003, 1.222)
	List Dedecker	0.325	-0.03	0.09	-0.172	0.406
	1056600	(-0.2, 0.858)	(-0.264, 0.192)	(0.023, 0.15)	(-0.393, 0.031)	(-0.143, 1.041)
	New Flemish	1.098	0.045	0.089	-0.088	-0.483
	1056913	(0.577, 1.628)	(-0.181, 0.282)	(0.027, 0.157)	(-0.294, 0.132)	(-1.084, 0.139)
	Social Liberal	0.282	-0.086	0.084	-0.1	0.597
	1056328	(-0.226, 0.83)	(-0.316, 0.133)	(0.018, 0.146)	(-0.307, 0.126)	(-0.05, 1.159)

	Socialist Different	1.184	-0.046	0.031	-0.179	1.045
	1056327	(0.666, 1.727)	(-0.269, 0.183)	(-0.033, 0.097)	(-0.391, 0.047)	(0.472, 1.679)
	Worker's	0.399	-0.051	0.072	-0.146	0.579
	1056222	(-0.119, 0.941)	(-0.287, 0.168)	(0.006, 0.134)	(-0.361, 0.068)	(-0.042, 1.193)
Bulgaria	Blue Coalition (SDS-DSB)	-0.491	0.53	0.124	0.195	0.272
	1100001	(-1, 0.086)	(0.268, 0.809)	(0.054, 0.19)	(-0.024, 0.404)	(-0.835, 1.405)
	European Development	1.281	-0.262	-0.013	0.352	-0.23
	1100600	(0.734, 1.818)	(-0.528, 0.011)	(-0.079, 0.058)	(0.142, 0.558)	(-1.33, 0.858)
	Coalition for Bulgaria	-0.133	-0.144	-0.045	-0.271	-0.332
	1100300	(-0.711, 0.396)	(-0.411, 0.124)	(-0.113, 0.024)	(-0.497, -0.07)	(-1.386, 0.785)
	Movement for Rights	-2.301	0.581	-0.179	-0.018	0.061
	1100900	(-2.847, -1.748)	(0.312, 0.856)	(-0.249, -0.114)	(-0.236, 0.194)	(-1.058, 1.211)
	NAPRED	-1.739	0.195	-0.001	0.122	0.393
	1100002	(-2.273, -1.2)	(-0.088, 0.459)	(-0.071, 0.065)	(-0.08, 0.334)	(-0.66, 1.535)
	Stability & Progress	-1.464	0.474	0.002	0.345	-0.536
	1100400	(-1.978, -0.902)	(0.212, 0.742)	(-0.067, 0.072)	(0.129, 0.559)	(-1.639, 0.61)
	National Union Attack	-1.297	-0.11	-0.055	0.296	-0.063
	1100700	(-1.825, -0.732)	(-0.376, 0.17)	(-0.122, 0.014)	(0.075, 0.506)	(-1.131, 1.052)
	Order, Lawfulness & Justice	-1.206	0.113	0.003	0.113	0.19
	1100601	(-1.73, -0.656)	(-0.158, 0.376)	(-0.066, 0.069)	(-0.112, 0.319)	(-0.914, 1.26)
Cyprus	Democrat	0.727	0.186	-0.102	0.207	-0.64
	1196422	(0.173, 1.246)	(-0.051, 0.451)	(-0.18, -0.025)	(0.002, 0.401)	(-1.592, 0.208)
	Democratic Rally	1.563	0.425	-0.067	0.509	-0.152
	1196711	(1.043, 2.147)	(0.178, 0.683)	(-0.147, 0.011)	(0.304, 0.704)	(-1.069, 0.726)
	Green	0.378	0.612	0.157	-0.074	0.57
	1196110	(-0.15, 0.932)	(0.361, 0.864)	(0.074, 0.232)	(-0.27, 0.131)	(-0.328, 1.478)
	European	-0.4	0.233	0.07	0.137	0.478
	1196600	(-0.934, 0.151)	(-0.01, 0.487)	(-0.006, 0.152)	(-0.073, 0.337)	(-0.378, 1.439)
	Social Democrat	0.43	0.101	0.029	-0.017	-0.22
	1196322	(-0.12, 0.955)	(-0.152, 0.355)	(-0.057, 0.103)	(-0.219, 0.194)	(-1.127, 0.673)
	Progressive	1.743	-0.254	-0.114	-0.513	0.491
	1196321	(1.209, 2.299)	(-0.509, -0.005)	(-0.195, -0.036)	(-0.714, -0.309)	(-0.383, 1.436)
Czech Republic	Christian Democrat	-0.407	-0.129	-0.031	-0.014	-0.149
	1203523	(-0.929, 0.134)	(-0.396, 0.121)	(-0.094, 0.024)	(-0.207, 0.186)	(-1.12, 0.848)
	Civic Democrat	1.212	0.421	0.053	0.732	-0.049
	1203413	(0.676, 1.747)	(0.157, 0.673)	(-0.005, 0.11)	(0.531, 0.923)	(-1.018, 0.932)
	Communist	-0.616	-0.198	-0.004	-0.379	0.459
	1203220	(-1.117, -0.051)	(-0.455, 0.061)	(-0.06, 0.057)	(-0.58, -0.18)	(-0.586, 1.409)
	Social Democrat	0.889	-0.199	-0.02	-0.334	0.196
	1203320	(0.337, 1.404)	(-0.447, 0.068)	(-0.081, 0.034)	(-0.524, -0.128)	(-0.807, 1.156)
	Green	-0.293	-0.033	-0.011	0.243	-0.442

	1203110	(-0.833, 0.212)	(-0.293, 0.226)	(-0.068, 0.048)	(0.04, 0.43)	(-1.421, 0.519)
Denmark	Conservative	-0.152	-0.052	0.029	0.695	-0.268
	1208620	(-0.709, 0.382)	(-0.29, 0.193)	(-0.009, 0.068)	(0.496, 0.912)	(-1.12, 0.568)
	People's	0.306	-0.454	-0.131	-0.134	0.155
	1208720	(-0.247, 0.848)	(-0.694, -0.197)	(-0.169, -0.092)	(-0.344, 0.079)	(-0.714, 1)
	Social Liberal	-0.749	0.273	0.068	0.223	0.864
	1208410	(-1.308, -0.191)	(0.019, 0.524)	(0.03, 0.107)	(0.011, 0.432)	(0.049, 1.736)
	June	-1.843	0.072	0.023	-0.211	0.16
	1208055	(-2.405, -1.301)	(-0.165, 0.334)	(-0.015, 0.062)	(-0.416, -0.002)	(-0.708, 0.989)
	Liberal Alliance	-2.254	0.133	-0.005	0.187	0.266
	1208421	(-2.807, -1.709)	(-0.109, 0.377)	(-0.045, 0.032)	(-0.029, 0.39)	(-0.584, 1.089)
	Liberal	0.894	-0.082	-0.068	0.745	-0.52
	1208420	(0.345, 1.437)	(-0.33, 0.159)	(-0.106, -0.028)	(0.527, 0.952)	(-1.377, 0.32)
	Social Democrat	1.986	0.099	0.028	-0.606	0.638
	1208320	(1.438, 2.554)	(-0.17, 0.336)	(-0.014, 0.064)	(-0.803, -0.399)	(-0.17, 1.504)
	Socialist	1.451	0.12	0.109	-0.546	0.67
	1208330	(0.917, 2.029)	(-0.128, 0.365)	(0.07, 0.148)	(-0.754, -0.333)	(-0.142, 1.519)
Estonia	Centre	0.134	0.304	-0.149	-0.396	3.577
	1233411	(-0.386, 0.687)	(0.056, 0.569)	(-0.227, -0.064)	(-0.603, -0.184)	(3.048, 4.08)
	Greens	0.695	-0.139	0.001	0.2	-1.232
	1233100	(0.143, 1.203)	(-0.402, 0.121)	(-0.08, 0.082)	(-0.013, 0.41)	(-1.75, -0.73)
	Reform	0.487	0.111	0.001	0.737	-1.79
	1233430	(-0.031, 1.033)	(-0.139, 0.38)	(-0.08, 0.082)	(0.53, 0.951)	(-2.276, -1.264)
	People's Union	-0.67	0.002	-0.143	0.146	-0.56
	1233612	(-1.192, -0.116)	(-0.254, 0.271)	(-0.228, -0.066)	(-0.05, 0.368)	(-1.07, -0.062)
	Social Democrat	1.047	0.003	0.111	0.185	-1.618
	1233410	(0.531, 1.592)	(-0.265, 0.264)	(0.034, 0.193)	(-0.02, 0.394)	(-2.106, -1.046)
	Pro Patria & Res Publica	0.76	-0.183	0.035	0.666	-2.253
	1233613	(0.2, 1.277)	(-0.444, 0.064)	(-0.05, 0.111)	(0.459, 0.875)	(-2.776, -1.755)
Finland	Centre	0.784	-0.427	-0.05	0.326	-0.485
	1246810	(0.24, 1.325)	(-0.696, -0.16)	(-0.123, 0.023)	(0.126, 0.539)	(-1.628, 0.603)
	Christian Democrat	-0.674	-0.027	0.004	0.126	-0.171
	1246520	(-1.223, -0.128)	(-0.294, 0.237)	(-0.07, 0.074)	(-0.076, 0.348)	(-1.336, 0.879)
	Green	1.937	0.728	0.204	-0.311	0.84
	1246110	(1.396, 2.483)	(0.458, 0.986)	(0.129, 0.275)	(-0.52, -0.098)	(-0.311, 2.023)
	Left	-0.375	0.288	0.035	-0.686	0.52
	1246223	(-0.936, 0.16)	(0.031, 0.558)	(-0.036, 0.109)	(-0.894, -0.481)	(-0.544, 1.703)
	National Coalition	2.003	-0.087	0.126	1.07	-1.021
	1246620	(1.452, 2.546)	(-0.344, 0.19)	(0.056, 0.202)	(0.867, 1.286)	(-2.206, 0.139)
	Social Democrat	1.184	-0.023	-0.006	-0.562	0.608
	1246320	(0.638, 1.737)	(-0.282, 0.246)	(-0.077, 0.067)	(-0.787, -0.366)	(-0.549, 1.767)
	Swedish People's	-1.102	0.582	0.072	0.075	0.391
	1246901	(-1.631, -0.53)	(0.311, 0.846)	(0, 0.145)	(-0.141, 0.268)	(-0.778, 1.483)
	True Finns	-0.096	-0.373	-0.169	-0.288	0.435

	1246820	(-0.65, 0.448)	(-0.645, -0.109)	(-0.239, -0.094)	(-0.508, -0.086)	(-0.67, 1.58)
France	Democrat	-0.111	0.052	0.083	-0.072	0.475
	1250336	(-0.648, 0.415)	(-0.203, 0.289)	(0.015, 0.164)	(-0.28, 0.119)	(-0.222, 1.19)
	New Anticapitalist & Workers' Struggle	-0.82	0.056	0.019	-0.472	-0.23
	1250226	(-1.345, -0.293)	(-0.181, 0.304)	(-0.056, 0.092)	(-0.67, -0.267)	(-0.931, 0.512)
	Communist	-0.906	0.106	-0.04	-0.49	0.486
	1250220	(-1.436, -0.388)	(-0.136, 0.354)	(-0.115, 0.031)	(-0.679, -0.275)	(-0.22, 1.212)
	Left Party	0.087	0.083	-0.051	-0.416	0.848
	1250337	(-0.455, 0.61)	(-0.151, 0.333)	(-0.121, 0.025)	(-0.617, -0.213)	(0.169, 1.609)
	National Front	-1.521	-0.225	-0.051	-0.155	-0.312
	1250720	(-2.05, -1.009)	(-0.451, 0.031)	(-0.126, 0.018)	(-0.355, 0.046)	(-1.053, 0.391)
	Socialist	1.211	0.095	0.053	-0.313	0.804
	1250320	(0.677, 1.738)	(-0.147, 0.341)	(-0.02, 0.121)	(-0.517, -0.113)	(0.063, 1.498)
	Greens	1.984	0.291	0.092	-0.134	0.014
	1250110	(1.465, 2.522)	(0.05, 0.542)	(0.02, 0.164)	(-0.333, 0.07)	(-0.685, 0.752)
	Popular (UMP)	1.032	0.107	-0.104	0.728	0.206
	1250626	(0.53, 1.591)	(-0.134, 0.359)	(-0.174, -0.028)	(0.537, 0.942)	(-0.471, 0.917)
Germany	Alliance '90 + Greens	0.819	0.437	0.208	0.088	0.02
	1276113	(0.29, 1.379)	(0.214, 0.661)	(0.124, 0.295)	(-0.123, 0.311)	(-0.593, 0.669)
	Christian Democrat	1.866	-0.16	-0.112	0.945	0.001
	1276521	(1.344, 2.431)	(-0.378, 0.067)	(-0.202, -0.023)	(0.724, 1.152)	(-0.619, 0.637)
	Free Democrat	0.474	-0.086	-0.026	0.659	0.206
	1276420	(-0.052, 1.047)	(-0.31, 0.133)	(-0.115, 0.059)	(0.44, 0.873)	(-0.389, 0.845)
	Social Democrat	1.447	0.103	-0.015	-0.035	0.398
	1276320	(0.924, 2.03)	(-0.108, 0.336)	(-0.106, 0.069)	(-0.239, 0.19)	(-0.221, 1.016)
	Left	-1.035	0.292	0.145	-0.471	0.063
	1276321	(-1.583, -0.502)	(0.084, 0.522)	(0.061, 0.232)	(-0.694, -0.266)	(-0.566, 0.674)
Greece	Radical Left	-0.567	0.411	0.108	-0.264	0.001
	1300215	(-1.077, -0.031)	(0.149, 0.677)	(0.036, 0.181)	(-0.465, -0.066)	(-0.917, 0.858)
	Communist	-0.141	-0.005	0.01	-0.335	-0.14
	1300210	(-0.652, 0.386)	(-0.272, 0.25)	(-0.062, 0.082)	(-0.532, -0.135)	(-1.025, 0.749)
	Greens	-0.101	0.098	0.054	0.039	-0.06
	1300116	(-0.64, 0.423)	(-0.154, 0.368)	(-0.02, 0.13)	(-0.168, 0.238)	(-0.959, 0.804)
	New Democracy	0.503	-0.264	-0.121	0.557	-0.247
	1300511	(-0.036, 1.01)	(-0.532, -0.007)	(-0.192, -0.047)	(0.366, 0.753)	(-1.12, 0.623)
	Socialist	0.88	-0.116	-0.133	-0.102	-0.496
	1300313	(0.342, 1.393)	(-0.375, 0.143)	(-0.203, -0.057)	(-0.305, 0.099)	(-1.39, 0.346)
	Popular Orthodox	-0.79	-0.257	-0.066	0.077	0.316
	1300703	(-1.318, -0.27)	(-0.516, 0.008)	(-0.143, 0.004)	(-0.127, 0.27)	(-0.615, 1.16)
Hungary	Free Democrats	-1.402	0.189	0.017	0.16	0.104
	1348422	(-1.955, -0.837)	(-0.117, 0.446)	(-0.046, 0.08)	(-0.077, 0.384)	(-0.719, 1.03)
	Christian Democrat	0	-0.023	-0.026	0.324	0.647

	1348526	(-0.54, 0.581)	(-0.308, 0.266)	(-0.086, 0.038)	(0.092, 0.558)	(-0.216, 1.525)
	Fidesz-Hungarian	2.799	-0.152	-0.11	-0.055	0.548
	1348421	(2.239, 3.356)	(-0.457, 0.109)	(-0.168, -0.043)	(-0.281, 0.187)	(-0.287, 1.451)
	Communist	-1.672	0.083	-0.028	-0.014	-0.057
	1348210	(-2.229, -1.128)	(-0.199, 0.35)	(-0.09, 0.036)	(-0.257, 0.208)	(-0.894, 0.867)
	Democratic Forum	-1.044	0.185	0.057	0.036	0.143
	1348521	(-1.588, -0.494)	(-0.094, 0.464)	(-0.008, 0.116)	(-0.208, 0.26)	(-0.704, 0.989)
	Socialist	-0.207	0.305	0.027	0.087	0.097
	1348220	(-0.735, 0.352)	(0.022, 0.577)	(-0.033, 0.092)	(-0.147, 0.323)	(-0.744, 0.965)
	Better Hungary	0.171	-0.182	0.008	0.096	-0.162
	1348700	(-0.395, 0.706)	(-0.451, 0.099)	(-0.054, 0.072)	(-0.144, 0.324)	(-1.01, 0.714)
Ireland	Fiann Fail	0.27	-0.117	-0.05	0.226	0.069
	1372620	(-0.237, 0.817)	(-0.343, 0.13)	(-0.127, 0.021)	(0.018, 0.436)	(-0.596, 0.719)
	Fine Gael	2.17	-0.032	0.079	0.378	-1.022
	1372520	(1.648, 2.71)	(-0.264, 0.2)	(0.01, 0.151)	(0.158, 0.583)	(-1.683, -0.33)
	Green	0.285	0.142	0.14	0.014	0.199
	1372110	(-0.232, 0.815)	(-0.1, 0.371)	(0.07, 0.217)	(-0.192, 0.22)	(-0.465, 0.885)
	Labour	2.207	0.22	0.048	-0.291	-0.128
	1372320	(1.703, 2.762)	(-0.027, 0.451)	(-0.029, 0.119)	(-0.497, -0.087)	(-0.77, 0.555)
	Libertas	-1.173	-0.096	-0.03	-0.311	0.583
	1372001	(-1.7, -0.638)	(-0.34, 0.139)	(-0.1, 0.047)	(-0.52, -0.099)	(-0.082, 1.24)
	Sinn Fein	-0.469	-0.13	-0.178	-0.407	0.479
	1372951	(-0.982, 0.083)	(-0.383, 0.093)	(-0.251, -0.109)	(-0.621, -0.2)	(-0.161, 1.148)
Italy	Communist Refoundation	-0.398	0.097	-0.014	-0.147	0.683
	1380212	(-0.935, 0.138)	(-0.135, 0.339)	(-0.085, 0.053)	(-0.378, 0.066)	(-0.352, 1.767)
	Democrat	1.223	0.322	0.104	-0.18	-0.666
	1380331	(0.699, 1.773)	(0.074, 0.554)	(0.033, 0.173)	(-0.405, 0.059)	(-1.698, 0.427)
	Italy of Values	0.491	0.286	0.039	-0.315	0.647
	1380902	(-0.04, 1.039)	(0.041, 0.521)	(-0.028, 0.107)	(-0.533, -0.076)	(-0.375, 1.741)
	Left & Freedom	-0.186	0.158	0.042	-0.174	0.03
	1380007	(-0.72, 0.368)	(-0.075, 0.387)	(-0.028, 0.111)	(-0.412, 0.037)	(-0.974, 1.13)
	Northern League	0.267	-0.251	-0.077	0.127	0.215
	1380720	(-0.298, 0.794)	(-0.491, -0.017)	(-0.148, -0.009)	(-0.108, 0.349)	(-0.828, 1.27)
	People of Freedom	1.298	-0.437	-0.032	0.351	-0.026
	1380630	(0.772, 1.842)	(-0.675, -0.204)	(-0.105, 0.035)	(0.121, 0.577)	(-1.113, 0.991)
	Right	-0.315	-0.063	-0.12	0.151	-0.099
	1380631	(-0.89, 0.189)	(-0.306, 0.173)	(-0.189, -0.05)	(-0.087, 0.378)	(-1.121, 1.017)
	Christian & Centre Democrats	-0.408	0.026	-0.042	0.177	-0.183
	1380523	(-0.926, 0.139)	(-0.193, 0.28)	(-0.111, 0.025)	(-0.035, 0.427)	(-1.248, 0.859)
Latvia	Civic Union	0.338	-0.139	-0.014	0.024	-1.35
	1428611	(-0.204, 0.878)	(-0.418, 0.118)	(-0.112, 0.078)	(-0.174, 0.229)	(-1.943, -0.756)
	Fatherland & Freedom	-0.649	-0.204	-0.03	0.19	-1.471

	1428723	(-1.208, -0.112)	(-0.475, 0.064)	(-0.124, 0.068)	(-0.016, 0.396)	(-2.039, -0.881)
	Human Rights	-1.041	0.048	-0.102	0.107	1.409
	1428422	(-1.603, -0.49)	(-0.218, 0.32)	(-0.199, -0.008)	(-0.086, 0.322)	(0.794, 1.952)
	Harmony Centre	0.339	0.387	-0.118	-0.251	2.868
	1428317	(-0.193, 0.9)	(0.129, 0.671)	(-0.221, -0.031)	(-0.453, -0.048)	(2.259, 3.435)
	Latvian Way	-0.613	0.438	-0.101	0.398	0.578
	1428424	(-1.152, -0.059)	(0.18, 0.715)	(-0.202, -0.013)	(0.206, 0.605)	(-0.026, 1.152)
	New Era	0.053	-0.206	-0.042	0.472	-1.422
	1428423	(-0.513, 0.613)	(-0.486, 0.045)	(-0.135, 0.055)	(0.261, 0.673)	(-2.017, -0.86)
	People's	-1.608	-0.121	-0.136	0.282	-0.447
	1428610	(-2.158, -1.059)	(-0.377, 0.154)	(-0.229, -0.037)	(0.074, 0.488)	(-1.032, 0.126)
	Society for Other Politics	-0.168	-0.324	-0.037	0.345	-0.83
	1428425	(-0.713, 0.37)	(-0.588, -0.066)	(-0.13, 0.063)	(0.131, 0.55)	(-1.399, -0.256)
	Green & Farmers	-0.259	-0.403	-0.135	0.387	-0.906
	1428110	(-0.79, 0.329)	(-0.665, -0.129)	(-0.235, -0.042)	(0.185, 0.592)	(-1.505, -0.328)
Lithuania	Lithuania's Poles	-1.7	0.089	-0.064	0.008	0.983
	1440952	(-2.24, -1.155)	(-0.208, 0.386)	(-0.133, 0.004)	(-0.184, 0.213)	(0.088, 1.914)
	Christian Democrat	0.8	0.238	0.003	0.563	-1.293
	1440620	(0.254, 1.339)	(-0.056, 0.54)	(-0.062, 0.073)	(0.361, 0.766)	(-2.247, -0.407)
	Labour	0.359	-0.307	-0.137	0.116	0.453
	1440322	(-0.161, 0.909)	(-0.591, -0.011)	(-0.202, -0.066)	(-0.084, 0.319)	(-0.502, 1.328)
	Liberal & Centre	-0.324	0.161	0.046	0.244	0.302
	1440420	(-0.853, 0.213)	(-0.121, 0.448)	(-0.02, 0.114)	(0.042, 0.43)	(-0.598, 1.234)
	Liberals' Movement	-0.189	0.393	0.087	0.171	-0.347
	1440421	(-0.719, 0.359)	(0.069, 0.667)	(0.018, 0.151)	(-0.017, 0.387)	(-1.226, 0.585)
	Peasant Popular	-0.679	-0.208	-0.086	-0.05	0.296
	1440824	(-1.231, -0.131)	(-0.51, 0.076)	(-0.152, -0.017)	(-0.253, 0.145)	(-0.604, 1.273)
	National Resurrection	-1.459	-0.127	-0.086	0.315	-0.418
	1440001	(-1.986, -0.894)	(-0.408, 0.194)	(-0.151, -0.015)	(0.111, 0.515)	(-1.292, 0.538)
	Social Liberals	-0.513	-0.074	-0.058	0.108	-0.156
	1440410	(-1.073, 0.013)	(-0.357, 0.216)	(-0.128, 0.01)	(-0.092, 0.311)	(-1.078, 0.752)
	Order & Justice	0.267	-0.394	-0.145	-0.124	0.31
	1440021	(-0.263, 0.818)	(-0.666, -0.092)	(-0.213, -0.079)	(-0.325, 0.081)	(-0.6, 1.204)
	Social Democrat	1.08	-0.17	-0.044	0.128	-0.208
	1440320	(0.531, 1.621)	(-0.459, 0.13)	(-0.106, 0.027)	(-0.074, 0.332)	(-1.167, 0.694)
Luxembourg	Alternative Democratic Reform	-1.234	-0.145	-0.064	-0.031	0.739
	1442951	(-1.789, -0.705)	(-0.369, 0.059)	(-0.098, -0.033)	(-0.256, 0.202)	(0.29, 1.211)
	Christian Social	3.363	-0.282	-0.009	0.321	-0.582
	1442520	(2.782, 3.906)	(-0.487, -0.061)	(-0.044, 0.022)	(0.081, 0.546)	(-1.043, -0.093)
	Citizens' List	-2.047	0.076	-0.04	-0.088	0.535
	1442009	(-2.609, -1.47)	(-0.134, 0.292)	(-0.074, -0.007)	(-0.32, 0.15)	(0.06, 1.01)
	Communist	-1.873	-0.016	-0.021	-0.135	0.541
	1442220	(-2.438, -1.332)	(-0.228, 0.199)	(-0.054, 0.012)	(-0.371, 0.089)	(0.064, 1.016)
	Democrat	0.786	-0.083	0.033	0.32	-0.538

	1442420	(0.243, 1.359)	(-0.293, 0.144)	(0, 0.067)	(0.084, 0.556)	(-1.013, -0.068)
	Socialist	2.249	-0.005	-0.029	0.164	-0.966
	1442320	(1.688, 2.815)	(-0.218, 0.212)	(-0.062, 0.004)	(-0.068, 0.39)	(-1.456, -0.491)
	Greens	1.082	0.182	0.063	0.393	-0.581
	1442113	(0.557, 1.674)	(-0.029, 0.398)	(0.03, 0.096)	(0.165, 0.621)	(-1.06, -0.112)
	Left	-0.978	0.094	0.013	-0.21	-0.057
	1442222	(-1.528, -0.406)	(-0.119, 0.311)	(-0.021, 0.046)	(-0.456, 0.016)	(-0.553, 0.387)
Malta	Democratic Alternative	0.093	0.28	0.344	0.125	1.115
	1470100	(-0.573, 0.714)	(-0.005, 0.547)	(0.216, 0.465)	(-0.072, 0.333)	(0.215, 2.029)
	Labour	2.081	-0.429	-0.096	-0.81	0.038
	1470300	(1.435, 2.726)	(-0.7, -0.151)	(-0.217, 0.032)	(-1.009, -0.611)	(-0.866, 0.979)
	National Action	-1.585	-0.039	0.12	-0.004	0.272
	1470700	(-2.222, -0.947)	(-0.315, 0.226)	(-0.011, 0.245)	(-0.208, 0.198)	(-0.652, 1.162)
	Nationalist	2.585	0.736	0.197	0.771	0.747
	1470500	(1.91, 3.188)	(0.468, 1.022)	(0.069, 0.32)	(0.574, 0.981)	(-0.21, 1.673)
Netherlands	Christian Democrat	1.341	0.025	-0.063	0.342	-0.535
	1528521	(0.81, 1.897)	(-0.201, 0.244)	(-0.122, -0.011)	(0.142, 0.547)	(-1.345, 0.31)
	Christian Union	-0.484	-0.077	-0.07	0.045	0.237
	1528526	(-1.038, 0.045)	(-0.283, 0.158)	(-0.125, -0.011)	(-0.167, 0.244)	(-0.625, 1.036)
	Democrats '66	1.316	0.33	0.158	0.268	-0.005
	1528330	(0.761, 1.849)	(0.114, 0.56)	(0.098, 0.211)	(0.058, 0.467)	(-0.876, 0.793)
	Green Left	1.158	0.376	0.18	-0.271	0.524
	1528110	(0.616, 1.721)	(0.152, 0.593)	(0.126, 0.24)	(-0.469, -0.053)	(-0.308, 1.351)
	Labour	1.517	0.32	0.079	-0.281	0.731
	1528320	(0.962, 2.054)	(0.104, 0.545)	(0.026, 0.137)	(-0.482, -0.075)	(-0.143, 1.53)
	Animals	-0.289	0.095	-0.061	-0.452	0.687
	1528006	(-0.836, 0.249)	(-0.136, 0.31)	(-0.119, -0.007)	(-0.666, -0.253)	(-0.145, 1.502)
	Freedom	-0.524	-0.235	-0.125	-0.201	0.668
	1528600	(-1.055, 0.047)	(-0.454, -0.017)	(-0.181, -0.071)	(-0.413, 0.002)	(-0.16, 1.477)
	People's	0.54	-0.048	-0.019	0.662	-0.287
	1528420	(0.032, 1.114)	(-0.281, 0.166)	(-0.076, 0.034)	(0.455, 0.866)	(-1.072, 0.55)
	Proud of Netherlands	-1.434	-0.094	-0.109	0.037	-0.031
	1528726	(-1.981, -0.897)	(-0.317, 0.128)	(-0.168, -0.051)	(-0.166, 0.255)	(-0.879, 0.768)
	Reformed Political Party	-1.258	-0.115	-0.09	-0.071	0.216
	1528527	(-1.827, -0.746)	(-0.342, 0.106)	(-0.145, -0.032)	(-0.273, 0.141)	(-0.581, 1.036)
	Socialist	0.85	0.144	0.077	-0.573	0.36
	1528220	(0.312, 1.394)	(-0.073, 0.371)	(0.023, 0.136)	(-0.784, -0.366)	(-0.471, 1.199)
Poland	Civic Platform	1.56	0.67	0.134	0.369	-0.418
	1616435	(1.029, 2.1)	(0.378, 0.972)	(0.067, 0.201)	(0.141, 0.578)	(-1.515, 0.64)
	CenterLeft Coalition	-1.487	0.097	0.008	0.095	0.444
	1616011	(-2.02, -0.967)	(-0.187, 0.387)	(-0.059, 0.075)	(-0.118, 0.308)	(-0.594, 1.445)
	Democratic Left	-0.133	0.202	0.055	0.094	0.363
	1616210	(-0.643, 0.419)	(-0.097, 0.478)	(-0.013, 0.118)	(-0.111, 0.316)	(-0.703, 1.44)
	Law & Justice	-0.091	-0.413	-0.042	-0.221	-0.16

	1616436	(-0.633, 0.427)	(-0.688, -0.123)	(-0.107, 0.022)	(-0.442, 0.003)	(-1.224, 0.909)
	Libertas	-1.998	0.145	-0.04	-0.001	-0.156
	1616010	(-2.54, -1.484)	(-0.132, 0.443)	(-0.103, 0.027)	(-0.21, 0.218)	(-1.266, 0.849)
	People's	-0.583	-0.169	-0.093	-0.023	-0.031
	1616811	(-1.12, -0.078)	(-0.457, 0.112)	(-0.162, -0.029)	(-0.243, 0.185)	(-1.088, 1.039)
Portugal	People's	0.061	-0.19	0.095	0.077	-0.012
	1620314	(-0.465, 0.633)	(-0.483, 0.061)	(0.007, 0.182)	(-0.147, 0.316)	(-1.122, 1.077)
	Democratic Union (Communist + Green)	-0.403	0.135	0.089	-0.505	0.237
	1620229	(-0.976, 0.133)	(-0.15, 0.4)	(0, 0.174)	(-0.729, -0.295)	(-0.866, 1.296)
	Left Bloc	0.89	0.157	0.312	-0.373	0.103
	1620211	(0.346, 1.469)	(-0.123, 0.432)	(0.225, 0.4)	(-0.601, -0.148)	(-1.002, 1.227)
	Social Democrat	1.684	-0.162	0.016	0.268	0.623
	1620313	(1.127, 2.222)	(-0.425, 0.112)	(-0.07, 0.101)	(0.034, 0.486)	(-0.506, 1.707)
	Socialist	0.664	0.265	-0.095	0.016	0.12
	1620311	(0.115, 1.227)	(-0.01, 0.528)	(-0.181, -0.009)	(-0.2, 0.24)	(-0.95, 1.284)
Romania	Christian Democratic National Peasants	-1.346	0.238	-0.02	0.107	0.222
	1642800	(-1.87, -0.795)	(-0.016, 0.496)	(-0.073, 0.037)	(-0.088, 0.32)	(-0.895, 1.37)
	Conservative	-1.114	0.113	0.009	0.238	-0.092
	1642600	(-1.615, -0.536)	(-0.142, 0.369)	(-0.043, 0.066)	(0.031, 0.438)	(-1.251, 1.01)
	Democratic Liberal	1.04	-0.059	-0.013	0.407	0.441
	1642400	(0.498, 1.589)	(-0.309, 0.211)	(-0.07, 0.041)	(0.215, 0.618)	(-0.668, 1.586)
	Hungarians in Romania	-1.007	1.144	-0.103	0.185	0.681
	1642900	(-1.563, -0.468)	(0.875, 1.391)	(-0.16, -0.049)	(-0.01, 0.395)	(-0.488, 1.794)
	Greater Romania	-0.309	-0.044	-0.083	0.106	-0.407
	1642700	(-0.83, 0.255)	(-0.316, 0.2)	(-0.136, -0.026)	(-0.1, 0.306)	(-1.579, 0.677)
	National Liberal	0.26	0.401	0.049	0.327	0.322
	1642401	(-0.275, 0.798)	(0.146, 0.658)	(-0.006, 0.104)	(0.126, 0.533)	(-0.832, 1.448)
	Social Democrat	1.305	0.027	-0.102	0.086	-0.494
	1642300	(0.753, 1.861)	(-0.238, 0.282)	(-0.158, -0.049)	(-0.128, 0.281)	(-1.668, 0.617)
Slovakia	Christian Democrat	-0.643	0.067	-0.035	0.206	-0.537
	1703521	(-1.174, -0.122)	(-0.156, 0.298)	(-0.109, 0.037)	(-0.02, 0.426)	(-1.398, 0.419)
	Communist	-1.464	-0.098	-0.041	-0.147	-0.353
	1703222	(-1.973, -0.934)	(-0.334, 0.115)	(-0.113, 0.032)	(-0.375, 0.077)	(-1.298, 0.519)
	Social Democrat	2.062	-0.665	-0.171	-0.015	0.238
	1703423	(1.541, 2.587)	(-0.895, -0.437)	(-0.242, -0.097)	(-0.25, 0.197)	(-0.68, 1.132)
	Free Forum	-1.203	-0.001	0.027	-0.109	-0.602
	1703524	(-1.695, -0.633)	(-0.229, 0.222)	(-0.041, 0.102)	(-0.334, 0.11)	(-1.478, 0.298)
	People's	-1.238	-0.265	-0.113	0.045	-0.629
	1703711	(-1.774, -0.709)	(-0.483, -0.03)	(-0.181, -0.04)	(-0.194, 0.265)	(-1.463, 0.35)
	Democratic & Christian Union	0.307	0.306	0.209	0.326	-0.349

	1703523	(-0.221, 0.833)	(0.07, 0.522)	(0.139, 0.282)	(0.08, 0.543)	(-1.255, 0.55)
	National	-0.475	-0.469	-0.073	-0.114	-0.613
	1703710	(-0.998, 0.071)	(-0.688, -0.236)	(-0.144, 0.004)	(-0.336, 0.125)	(-1.553, 0.28)
	SMK	-1.467	0.782	-0.086	0.005	0.06
	1703954	(-1.966, -0.904)	(0.552, 1.023)	(-0.16, -0.015)	(-0.226, 0.234)	(-0.896, 0.927)
Slovenia	Pensioners'	-0.581	-0.269	-0.351	-0.004	0.069
	1705951	(-1.148, 0.098)	(-0.511, -0.011)	(-0.486, -0.209)	(-0.207, 0.218)	(-0.688, 0.882)
	For Real	1.064	0.09	0.186	0.248	0.039
	1705324	(0.389, 1.638)	(-0.159, 0.341)	(0.045, 0.325)	(0.024, 0.451)	(-0.802, 0.796)
	Liberal Democracy	0.661	0.059	0.098	0.186	0.42
	1705421	(0.025, 1.269)	(-0.183, 0.31)	(-0.041, 0.235)	(-0.019, 0.408)	(-0.389, 1.199)
	Christian People's	-0.972	0.255	-0.236	0.257	-1.045
	1705522	(-1.618, -0.392)	(0.022, 0.516)	(-0.37, -0.089)	(0.047, 0.467)	(-1.785, -0.223)
	Democrat	0.39	0.071	-0.366	0.218	-1.02
	1705320	(-0.242, 0.978)	(-0.172, 0.318)	(-0.514, -0.232)	(0.011, 0.425)	(-1.802, -0.215)
	National	-0.975	-0.236	-0.356	0.051	-0.561
	1705710	(-1.595, -0.373)	(-0.486, 0.015)	(-0.501, -0.223)	(-0.158, 0.265)	(-1.378, 0.216)
	People's	-0.859	-0.056	-0.199	0.131	-0.823
	1705521	(-1.444, -0.22)	(-0.302, 0.182)	(-0.349, -0.06)	(-0.067, 0.36)	(-1.608, -0.044)
	Social Democrat	2.19	0.035	0.158	0.159	-0.255
	1705323	(1.572, 2.805)	(-0.211, 0.284)	(0.016, 0.293)	(-0.048, 0.364)	(-1.102, 0.523)
	Youth	-0.485	0.119	-0.167	-0.061	0.2
	1705952	(-1.109, 0.121)	(-0.136, 0.354)	(-0.304, -0.028)	(-0.275, 0.146)	(-0.605, 1.002)
Spain	Basque Nationalist	-2.116	0.407	-0.016	-0.112	0.147
	1724902	(-2.661, -1.584)	(0.154, 0.665)	(-0.057, 0.028)	(-0.304, 0.102)	(-0.807, 1.132)
	Basque Social Democracy	-2.362	0.369	-0.018	-0.124	0.504
	1724903	(-2.889, -1.828)	(0.117, 0.629)	(-0.06, 0.028)	(-0.335, 0.084)	(-0.507, 1.441)
	Canarian	-2.083	0.095	-0.047	-0.082	-0.04
	1724907	(-2.613, -1.535)	(-0.156, 0.347)	(-0.089, -0.006)	(-0.296, 0.119)	(-0.972, 1.011)
	Convergence & Union	-1.639	0.553	-0.03	-0.185	-0.263
	1724007	(-2.178, -1.107)	(0.302, 0.818)	(-0.072, 0.014)	(-0.389, 0.026)	(-1.205, 0.732)
	Galician Nationalist	-2.06	0.095	-0.018	-0.09	-0.232
	1724908	(-2.592, -1.525)	(-0.175, 0.326)	(-0.06, 0.027)	(-0.309, 0.116)	(-1.221, 0.741)
	Navarre Yes	-2.357	0.249	-0.008	-0.114	0.244
	1724923	(-2.877, -1.796)	(-0.004, 0.509)	(-0.05, 0.035)	(-0.318, 0.096)	(-0.732, 1.185)
	Navarrese People's	-2.279	-0.001	-0.025	0.001	0.371
	1724922	(-2.793, -1.712)	(-0.268, 0.24)	(-0.069, 0.017)	(-0.207, 0.205)	(-0.589, 1.308)
	People's	1.794	-0.593	-0.026	0.424	0.265
	1724610	(1.258, 2.328)	(-0.834, -0.326)	(-0.069, 0.016)	(0.214, 0.625)	(-0.737, 1.216)
	Republican Left of Catalonia	-1.941	0.447	-0.015	-0.05	0.212
	1724905	(-2.483, -1.418)	(0.191, 0.704)	(-0.058, 0.027)	(-0.247, 0.167)	(-0.699, 1.201)
	Socialist Workers	1.447	-0.066	-0.039	-0.229	0.656
	1724320	(0.912, 2.007)	(-0.313, 0.187)	(-0.081, 0.003)	(-0.431, -0.025)	(-0.349, 1.584)

	Union, Progress	-0.148	-0.019	0.051	0.021	-0.244
	1724010	(-0.698, 0.385)	(-0.26, 0.245)	(0.008, 0.093)	(-0.181, 0.232)	(-1.178, 0.684)
	United Left	-0.354	0.512	0.017	-0.367	-0.231
	1724220	(-0.89, 0.2)	(0.253, 0.765)	(-0.026, 0.059)	(-0.578, -0.162)	(-1.195, 0.704)
Sweden	Centre	-0.131	0.047	0.034	0.276	-0.197
	1752810	(-0.656, 0.408)	(-0.192, 0.296)	(-0.055, 0.121)	(0.067, 0.476)	(-0.888, 0.476)
	Christian	-0.608	0.171	-0.018	0.286	-0.371
	1752520	(-1.104, -0.054)	(-0.076, 0.416)	(-0.104, 0.071)	(0.08, 0.484)	(-1.072, 0.273)
	Green	1.204	0.21	0.212	-0.359	0.695
	1752110	(0.67, 1.739)	(-0.025, 0.468)	(0.124, 0.297)	(-0.566, -0.156)	(0.007, 1.357)
	Left	0.046	0.188	0.126	-0.75	0.577
	1752220	(-0.46, 0.593)	(-0.05, 0.448)	(0.039, 0.21)	(-0.952, -0.53)	(-0.1, 1.233)
	Liberal	0.583	0.274	0.164	0.799	-0.119
	1752420	(0.062, 1.12)	(0.022, 0.509)	(0.074, 0.251)	(0.602, 1.01)	(-0.806, 0.53)
	Moderate	1.239	0.108	0.011	1.309	-0.895
	1752620	(0.715, 1.772)	(-0.143, 0.355)	(-0.073, 0.103)	(1.107, 1.523)	(-1.59, -0.25)
	Social Democrat	1.709	-0.148	-0.123	-0.971	0.474
	1752320	(1.174, 2.233)	(-0.395, 0.1)	(-0.207, -0.031)	(-1.189, -0.775)	(-0.208, 1.155)
	Democrats	-2.007	0.049	-0.068	0.005	0.561
	1752700	(-2.524, -1.455)	(-0.192, 0.304)	(-0.159, 0.017)	(-0.185, 0.223)	(-0.14, 1.224)
United Kingdom	British National	-1.593	-0.092	-0.1	0.079	0.058
	1826720	(-2.134, -1.051)	(-0.349, 0.165)	(-0.151, -0.046)	(-0.116, 0.287)	(-0.668, 0.777)
	Conservative	1.655	-0.557	-0.003	0.741	-0.19
	1826620	(1.146, 2.231)	(-0.8, -0.291)	(-0.057, 0.047)	(0.545, 0.943)	(-0.908, 0.511)
	Green	0.208	0.371	0.071	-0.191	0.394
	1826110	(-0.352, 0.726)	(0.107, 0.629)	(0.021, 0.123)	(-0.39, 0.015)	(-0.298, 1.105)
	Labour	0.654	0.408	0.119	-0.432	0.716
	1826320	(0.128, 1.189)	(0.168, 0.679)	(0.064, 0.169)	(-0.636, -0.226)	(0.037, 1.449)
	Liberal Democrat	1.022	0.294	0.097	0.265	0.028
	1826421	(0.488, 1.578)	(0.04, 0.555)	(0.04, 0.148)	(0.064, 0.458)	(-0.667, 0.757)
	Plaid Cymru	-2.257	0.124	-0.062	0.078	0.448
	1826901	(-2.796, -1.708)	(-0.123, 0.402)	(-0.116, -0.011)	(-0.115, 0.293)	(-0.268, 1.167)
	Scottish National	-1.921	0.081	-0.059	-0.094	0.844
	1826902	(-2.497, -1.403)	(-0.187, 0.326)	(-0.113, -0.006)	(-0.297, 0.111)	(0.107, 1.572)
	Independence	-0.413	-0.346	-0.105	-0.068	0.164
	1826951	(-0.994, 0.099)	(-0.608, -0.09)	(-0.157, -0.051)	(-0.271, 0.125)	(-0.518, 0.913)

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